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# Drivers of the change in carbon dioxide emissions under the progress of urbanization in 30 provinces in China: A decomposition analysis

Yuzhuo Huang [a], Ken'ichi Matsumoto [b,c,*]

[a] Graduate School of Fisheries and Environmental Sciences, Nagasaki University, 1–14 Bunkyo-machi, Nagasaki, 852-8521, Japan
[b] Faculty of Economics, Toyo University, 5–28–20 Hakusan, Bunkyo-ku, Tokyo, 112-8606, Japan
[c] Research Institute for Global Change, Japan Agency for Marine-Earth Science and Technology, 3173–25 Showa-machi, Kanazawa-ku, Yokohama, Kanagawa, 236-0001, Japan

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ABSTRACT

China's extensive and growing carbon dioxide ($CO_2$) emissions are linked to rapid economic development and advancing urbanization, posing serious concerns in the context of climate change. Decomposition analysis has been widely performed to identify the drivers of China's $CO_2$ emissions. However, to date, no researchers have examined the drivers of the change in $CO_2$ emissions under the progress of urbanization across all of its provinces. Using provincial statistical data and six key factors influencing $CO_2$ emissions (carbon intensity, energy intensity, resident consumption, consumption inhibition, population urbanization, and population size), we applied the logarithmic mean Divisia index decomposition method to examine how urbanization affect $CO_2$ emission changes across 30 provinces during 1990–2016. We elucidated that while urbanization's effects on $CO_2$ emissions increased in China as a whole during this period, they were regionally differentiated. The energy intensity effect was the main driver of reduced $CO_2$ emissions, with carbon intensity exerting weaker effects in the 30 provinces, differentiated by their energy structures. The resident consumption effect, strongly linked to advancing urbanization, was the primary driver of increased $CO_2$ emissions in all the provinces. While the consumption inhibition and population urbanization effects were positive at the national level, they were negative in highly urbanized provinces and in highly industrial provinces. These findings highlight the need to promote environmentally friendly consumption and to design regionally differentiated policies and optimized energy structures tailored to particular urbanization contexts. Moreover, they can provide valuable inputs for other developing countries undergoing continuous urbanization, contributing to efforts to balance economic development and environmental sustainability.

## 1. Introduction

Under economic globalization, China's economy has grown rapidly to become one of the most advanced economies. China's reduction of its carbon dioxide ($CO_2$) emissions would significantly contribute to efforts to solve the problem of climate change and to promote the sustainable development of the global economy (Gao, 2016). Accordingly, China, as a major carbon emitter, needs to assume a larger share of international responsibility. In the 2009 Copenhagen Accord, the Chinese government pledged to reduce the country's carbon intensity by 40%–45% from its 2005 level by 2020. Furthermore, in the 2015 Paris Agreement, China pledged to achieve peak $CO_2$ emissions and to reduce its emissions per gross domestic product (GDP) by 60%–65% from the 2005 level by 2030.

Urbanization is not only the outcome but also a cause of economic development (Gallup and Sachs, 2019). Economic globalization has contributed to the rapid development and accelerated urbanization of countries worldwide. Following China's implementation of its reform and opening-up policy, China's urban population increased from 172.4 to 792.9 million with the explosive growth of the economy from 1978 to 2016 (National Bureau of Statistics of China (2017)). At the same time, the country's urbanization rate rose from 17.9% to 58.5%, reflecting an average annual rate increase of nearly one percentage point. However, given an average urbanization rate of 72.6% for developed countries, China's urbanization still has further room for development in the future.

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* Corresponding author. Faculty of Economics, Toyo University, 5-28-20 Hakusan, Bunkyo-ku, Tokyo, 112-8606, Japan.
*E-mail address:* matsumoto1005@toyo.jp (K. Matsumoto).

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Advancing urbanization leads to an increase in $CO_2$ emissions to a great extent. Moreover, studies have found that the growth rate of the increment in $CO_2$ emissions is positively associated with the speed of urbanization (Sheng and Guo, 2016). In developing countries, urbanization is a key source of regional economic development, and its effect on $CO_2$ emissions will be extensive with the continuous expansion of the urban economy (Sheng and Guo, 2018). Meanwhile, the process of urbanization covers not only economic development but also energy, environment, and other aspects. From the onset of the 21st century, urbanization has expanded concurrently with China's economic advancement along with a surge in energy consumption. During 1978–2016, China's total energy consumption increased from 571.44 to 4,358.19 million tons of standard coal at an average annual growth rate of 5.5% (National Bureau of Statistics of China, 2017). Moreover, energy-intensive economic activities (e.g., manufacturing and transportation), which are driven primarily by fossil fuels and contribute to environmental degradation, may also be widespread in urban areas (Shahbaz et al., 2016).

Starting with the 12th Five-Year Plan (2011–2015), the Chinese government has increasingly emphasized the expansion of domestic demand, the main aim of which is to expand resident consumption to stabilize economic growth. Moreover, $CO_2$ emissions from resident consumption have emerged as important considerations in analyses of the drivers of $CO_2$ emissions (Dai et al., 2012). In some developed countries, residential energy consumption has exceeded industrial energy consumption since the 1990s and has been an important driver of the growth of $CO_2$ emissions (Zhu and Peng, 2012). The $CO_2$ emissions of resident consumption will inevitably increase over time with continually expanding urbanization. Therefore, the future urbanization and consumption trends of residents will gradually become the main determinants of China's $CO_2$ emission growth.

The effects of urbanization on $CO_2$ emissions are multiple and complex and vary according to the stage of urbanization (Zhou et al., 2019). The economic development strategies of China's internal provinces are different; thus, the stage of urbanization in different provinces is also different. How urbanization at different stages of development affects $CO_2$ emissions in all the provinces in China is the main research question of this study. In addition, most studies on the decomposition analysis of China's $CO_2$ emissions have focused on the national level or on a segment of China's regions. To the best of our knowledge, however, no previous researchers have evaluated the effects of urbanization on $CO_2$ emissions for the entire spectrum of provincial administrative units in China. Also, few studies have provided systematic evaluations of the drivers of $CO_2$ emissions in specific administrative units (Matsumoto et al., 2019; Shigetomi et al., 2018; Shiraki et al., 2020). To advance scientific knowledge regarding the effects of urbanization on $CO_2$ emissions from the perspective of resident consumption, we evaluated the effects of urbanization on the changes in $CO_2$ emissions during 1990–2016. A six-factor logarithmic mean Divisia index (LMDI) decomposition approach (carbon intensity, energy intensity, consumption inhibition, resident consumption, population urbanization, and population size) was applied in the 30 provincial administrative units (hereafter, provinces) across mainland China.[1] Our findings are of considerable value for improving the viability and application of effective strategies for reducing $CO_2$ emissions in China by accounting for regional differences and promoting economic and societal low-carbon development. Furthermore, the results of this study can provide insights with international applicability for reducing $CO_2$ emissions, especially in other developing countries.

The reminder of this paper is organized as follows. Section 2 offers a review of the literature, section 3 provides the methodology and the data, section 4 shows the results and a discussion, and section 5 presents conclusions and policy implications.

## 2. Literature review

Many studies have applied various types of decomposition analysis to evaluate the drivers of China's extensive $CO_2$ emissions. Considering the spatial dimension, we subdivided the previous studies focusing on China into two categories: national and provincial. Table 1 presents a summary of studies that have applied decomposition analysis to China's $CO_2$ emissions.

### *2.1. National level studies*

Industry produces the largest amount of $CO_2$ emissions; thus, many studies that have focused on the critical issue of China's $CO_2$ emissions have mainly been concentrated in the industrial sector. Xu et al. (2014) used the LMDI method to analyze the factors that influence $CO_2$ emissions due to fossil energy consumption in China and found that $CO_2$ emissions mostly arise from industry, while the other sectors generally exhibit good performance in reducing $CO_2$ emissions. Liang et al. (2019), who combined the LMDI method and the Tapio decoupling model to study the $CO_2$ emissions of China's industry and subsectors, showed that per capita output is the primary factor leading to increases in $CO_2$ emissions. Zhang et al. (2019) conducted a decomposition analysis of the drivers influencing China's $CO_2$ emissions by examining the details of 41 industry subsectors and found that energy intensity was the primary indicator that reduced $CO_2$ emissions. Lin and Long (2016) studied the factors influencing energy usage and $CO_2$ emissions within China's chemical industry based on the LMDI method and found that decreases in $CO_2$ emissions were related to energy intensity and energy structure.

An increasing number of studies have offered evaluations of the effects of urbanization and resident consumption on $CO_2$ emissions. Zhu and Wei (2013) studied the effects of urbanization on $CO_2$ emissions from the perspective of household consumption based on China's national data. They found that resident consumption in the progress of rapid urbanization has become an important driving force of China's $CO_2$ emissions. Xia et al. (2019) further confirmed that advancing urbanization not only increases household incomes but also promotes consumption, thereby constituting a new source of $CO_2$ emissions. Wang et al. (2019a, b) used a factor-reversible structural decomposition method to explore the effects of urbanization and changes in consumption patterns on incremental household $CO_2$ emissions. They pointed out that urbanization and changes in consumption patterns contributed to $CO_2$ emissions in China. Furthermore, based on the LMDI method, Ma et al. (2019) decomposed the energy-related $CO_2$ emissions in China and argued that rapid economic development and accelerated urbanization counter a reduction in $CO_2$ emissions.

### *2.2. Provincial level studies*

Compared with national level studies, provincial level studies on the influencing factors of $CO_2$ emissions are more targeted and representative. Zheng et al. (2019) conducted an LMDI decomposition analysis of $CO_2$ emissions in China's 30 provinces with aggregated eight regions. They found that the drivers of changes in $CO_2$ emissions varied across regions because of differences in their development patterns. Combining two-layer LMDI decomposition with Q-type hierarchical clustering, Jiang et al. (2017) systematically evaluated the contributions of related drivers from 30 provinces to the growth in China's national $CO_2$ emissions. They found that the contributions of various provinces to national $CO_2$ emission growth and their respective driving mechanisms differed considerably and changed dynamically over time. Wang et al. (2019a, b) applied a structural decomposition analysis (SDA) to explore the main factors contributing to indirect $CO_2$ emissions from resident

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[1] Because of constraints relating to data collection, we did not include the Tibet Autonomous Region or the Special Administrative Regions of Hong Kong and Macao. See Fig. A1 for the geographical coverage of the study.

**Table 1**

Studies using decomposition methods for examining $CO_2$ emissions and related topics in China (in chronological order).

| Literature | Region | Period | Decomposition method [a, b] | Decomposed variables and decomposition factors |
|---|---|---|---|---|
| Zhao et al. (2010) | Shanghai | 1996–2007 | IDA (LMDI) | ● Industrial $CO_2$ emissions<br>● Four factors: energy mix, energy intensity, industrial structure, and industrial outputs |
| Zhu and Wei (2013) | China | 1980–2010 | IDA (LMDI) | ● $CO_2$ emissions from energy consumption<br>● Six factors: population size, urbanization, household consumption, consumption restraint, energy intensity, and emission coefficient |
| Xu et al. (2014) | China | 1995–2011 | IDA (LMDI) | ● $CO_2$ emissions from energy consumption<br>● Five factors: energy structure, energy intensity, industrial structure, economic outputs, and population scale |
| Wang et al. (2014) | 30 provinces | 2005–2010 | Production-theoretical decomposition | ● Provincial total $CO_2$ emissions<br>● Seven factors: Changes in potential carbon factors, potential energy intensity, GDP, technical efficiency relating to $CO_2$ emissions, carbon abatement technology, technical efficiency relating to energy usage, and energy savings technology |
| Lin and Long (2016) | 30 provinces | 1980–2011 | IDA (LMDI) | ● Changes in $CO_2$ emissions in the chemical industrial sector<br>● Five factors: emission coefficient, energy structure, energy intensity, output per worker, and expansion scale |
| Zang et al. (2017) | Shanxi | 1995–2014 | IDA (LMDI) | ● Direct residential $CO_2$ emissions<br>● Seven factors: the number of households, per capita household income, household size, urbanization, energy intensity, energy structure, and emission coefficient |
| Pan et al. (2018) | Northeastern region, Central region, Western region, Coastal region | 2002–2010 | SDA | ● $CO_2$ emissions<br>● Three factors: carbon emissions intensity, production technology, and final demand |
| Shi et al. (2019) | Beijing, Tianjin, Shanghai, Chongqing | 2010–2015 | IDA (LMDI) | ● Per capita urban $CO_2$ emissions<br>● Nine factors: energy emissions, energy intensity, per capita energy emissions in the manufacturing and transportation sectors, transportation energy intensity, per capita vehicles, energy emissions, energy intensity, and per capita building areas in the construction sector |
| Feng et al. (2019) | Guangdong | 1995–2015 | LMDI (IDA) | ● $CO_2$ emissions<br>● Five factors: carbon intensity, energy structure, energy intensity, economic growth, and population growth |
| Ma et al. (2019) | China | 2005–2016 | IDA (LMDI) | ● $CO_2$ emissions<br>● Six factors: emission factor, energy structure, energy intensity of the industry, industrial structure, economic outputs, and population scale |
| Zheng et al. (2019) | Beijing-Tianjin, North and Northeast China, Central and South Coasts, Central, Southwest, and Northwest | 2000–2016 | IDA (LMDI) | ● $CO_2$ emissions<br>● Seven factors: population variations, economic growth, regional structure adjustment, energy efficiency improvement, industrial structure upgrades, energy mix, and changes in emission intensity |
| Wang et al. (2019a, b) | China | 2000–2015 | SDA | ● Total household $CO_2$ emissions<br>● Six factors: carbon intensity, structural change, rural consumption, urban consumption, population, and urbanization |
| Xia et al. (2019) | China | 1995–2009 | SDA | ● Indirect $CO_2$ emissions from household consumption<br>● Six factors: direct carbon emissions coefficient, technology, urbanization rate, urban population, consumption composition, and per capita consumption |
| Cao et al. (2019) | China and 30 provinces | 2007–2012 | SDA | ● National and regional carbon intensities<br>● Three factors: intensity (or efficiency), input structure, and final demand |
| Wang et al. (2019a, b) | Beijing, Tianjin, and Hebei | 2002–2012 | SDA | ● Indirect $CO_2$ emissions from urban and rural residential consumption<br>● Five factors: emission intensity, intermediate demand, consumption structure, consumption level, and population size |
| Wu et al. (2019) | China | 2000–2015 | IDA (LMDI) | ● $CO_2$ emissions from the construction sector<br>● Eight factors: emission factor, industrial structure, energy structure, energy demand from appliances, floor space, infrastructure capacity, infrastructure development, and road length |
| Zhang et al. (2021) | Three major cities in the middle reaches of the Yangtze River | 2000–2017 | IDA (LMDI based on the IPAT model) | ● $CO_2$ emissions from energy consumption<br>● Eight factors: urban expenditures, economics, industrial structure, population structure, land use effect, population density, energy intensity, and $CO_2$ emissions intensity |

Notes: [a]: This column only focuses on decomposition methods, although alternative methods were also applied in some studies.

[b]: IDA: index decomposition analysis; LMDI: logarithmic mean Divisia index; SDA: structural decomposition analysis.

consumption in the Beijing–Tianjin–Hebei region and found that the level of resident consumption and the carbon intensity were the main factors influencing indirect $CO_2$ emissions. Shi et al. (2019) decomposed per capita urban $CO_2$ emissions of Chinese megacities (Beijing, Tianjin, Shanghai, and Chongqing) to analyze the specific drivers, and showed that the development of manufacturing and the improvement of residential living standards in the cities led to an increase in $CO_2$ emissions. Feng et al. (2019) applied the LMDI method to investigate the drivers of $CO_2$ emissions in Guangdong Province and showed that both economic and demographic growth had a positive impact on $CO_2$ emissions.

The existing studies on the effects of urbanization and resident consumption on $CO_2$ emissions have mainly focused on individual regions as opposed to considering all provinces. Based on the LMDI method, Zang et al. (2017) explored the effects of urbanization and household-related factors on residents' direct $CO_2$ emissions in Shanxi Province and demonstrated that urbanization expansion marginally contributed to increased $CO_2$ emissions. Zhang et al. (2021) used the LMDI based on the impact, population, affluence, and technology (IPAT) model to decompose the factors that affect $CO_2$ emissions due to energy consumption in three major cities (Wuhan, Changsha, and Nanchang) in the middle reaches of the Yangtze River. They found that urbanization expansion is more significant than economic growth in promoting $CO_2$ emissions.

## 3. Methodology and data

Using provincial level data during 1990–2016, we applied the LMDI approach to conduct a quantitative evaluation of the effects of urbanization on $CO_2$ emissions considering resident consumption.

### 3.1. LMDI decomposition method

Fig. 1 depicts the analytical structure. We defined three major decomposition categories: energy, consumption, and population. Accordingly, six factors were identified to explore the effects on $CO_2$ emissions. The connections of resident consumption and population urbanization to the overall urbanization process were particularly strong.

Decomposition analysis is a mainstream method used for quantitative measurement of the contribution of factors driving energy consumption and $CO_2$ emissions (Li et al., 2017). Commonly used decomposition methods include index decomposition analysis (IDA) and SDA. Because IDA is based on terminal output data, it is easier to conduct an analysis using a smaller data sample. The LMDI, which is a variant of IDA, is a decomposition method entailing few variables and involving a time series. Because this modeling method does not rely on input–output data, it has gained in popularity since 2000 (Ang, 2015). The LMDI can be easily formulated, can effectively process the zero-valued and negative-valued data, and has the advantage of being constant sum for the decomposition results of multiplication and addition (Fan and Zhou, 2019). In addition, compared with other factor decomposition methods, the decomposed results of LMDI are more accurate and convincing (Ang, 2005). Therefore, we chose LMDI as the research method.

Considering the Kaya identity, we decomposed $CO_2$ emissions as follows:

$$CARB_i=\frac{CARB_i}{ENE_i}\times\frac{ENE_i}{GRP_i}\times\frac{GRP_i}{POP_i}\times POP_i \tag{1}$$

where $CARB$ denotes $CO_2$ emissions (in units of 10,000 tons), $ENE$ denotes total energy consumption (10,000 tons of standard coal), $GRP$ denotes the gross regional product (GRP; 100 million yuan),[2] $POP$ denotes the population (in units of 10,000 people), and $i$ denotes 30 provinces.

Because our aim was to analyze the effects of the relevant factors on $CO_2$ emissions, focusing mainly on urbanization, we incorporated resident consumption and population urbanization factors in the traditional Kaya identity and further expanded them in a vector form to include urban and rural areas. Consequently, we inserted residential consumption ($RES$) into eq. (1) as follows:

$$CARB_i=\frac{CARB_i}{ENE_i}\times\frac{ENE_i}{GRP_i}\times\frac{GRP_i}{RES_i}\times\frac{RES_i}{POP_i}\times POP_i \tag{2}$$

Urbanization can be conceived simply as an increase in the ratio of the urban population. Therefore, considering the urban–rural population structure, we subdivided $RES$ and $POP$ into their urban and rural components. Thus, $RES\_u$ and $RES\_r$ denotes resident consumption in urban and rural areas, respectively. Similarly, $POP\_u$ and $POP\_r$ denotes the urban and rural populations, respectively.[3] Accordingly, we expressed $RES$ as follows:

$$RES_{\mathrm{i}}=\left(\frac{RES\_\mathrm{u}_i}{POP\_u_{\mathrm{i}}}\ \frac{RES\_r_i}{POP\_r_i}\right)\times\begin{pmatrix}\dfrac{POP\_u_i}{POP_i}\\[2ex]\dfrac{POP\_r_{\mathrm{i}}}{POP_i}\end{pmatrix}\times POP_i \tag{3}$$

We subsequently plugged eq. (3) into eq. (2) to obtain the following equation:

$$\begin{aligned}CARB_i&=\frac{CARB_i}{ENE_i}\times\frac{ENE_i}{GRP_i}\times\frac{GRP_i}{RES_i}\times\left(\frac{RES\_u_i}{POP\_u_i}\ \frac{RES\_r_i}{POP\_r_i}\right)\times\begin{pmatrix}\dfrac{POP\_u_i}{POP_i}\\[2ex]\dfrac{POP\_r_i}{POP_i}\end{pmatrix}\times POP_i\\&=C\_int_i\times E\_int_i\times C\_inb_i\times(PC\_con\_u_iPC\_con\_r_i)\times\begin{pmatrix}P\_pop\_u_{\mathrm{i}}\\P\_pop\_r_i\end{pmatrix}\times POP_i\end{aligned} \tag{4}$$

where $C\_int$ denotes carbon intensity ($CARB/ENE$), $E\_int$ denotes energy intensity ($ENE/GRP$), $C\_inb$ represents the inhibition of consumption ($GRP/RES$), $PC\_con\_u$ ($PC\_con\_r$) refers to urban (rural) per capita consumption ($RES\_u/POP\_u$ ($RES\_r/POP\_r$)), and $P\_pop\_u$ ($P\_pop\_r$) refers to the proportion of the urban (rural) population in relation to the total population ($POP\_u/POP$ ($POP\_r/POP$)). $S\_u_i = (R\_con\_u_i \times P\_pro\_u_i)/(R\_con\_u_i \times P\_pro\_u_i + R\_con\_r_i \times P\_pro\_r_i)$, which denotes the proportion of the consumption of urban residents in relation to the total consumption of the province; this was plugged into eq. (4), as follows:

$$\begin{aligned}CARB_i&=C\_int_i\times E\_int_i\times C\_inb_i\times P\_con\_u_i^{S\_u_i}\times P\_con\_r_i^{1-S\_u_i}\\&\times PC\_con\_u_i^{S\_u_i}\times PC\_con\_r_i^{1-S\_u_i}\times P\_pop\_u_i^{S\_u_i}\times P\_pop\_r_i^{1-S\_u_i}\times POP_i\end{aligned} \tag{5}$$

where $P\_con\_u$ ($P\_con\_r$) refers to the inverse of the proportion of the urban (rural) consumption in relation to the total consumption ($RES/RES\_u$ ($RES/RES\_r$)).

This equation shows the product form of $CO_2$ emissions. Applying the LMDI approach, we obtained the effect of each factor on $CO_2$ emissions (eqs. (6)–(12)). Equation (5) decomposes $CO_2$ emissions at one point in time, whereas eq. (6) decomposes the differences in $CO_2$ emissions between two time points.

Total effect:

$$\Delta CARB_i^T=CARB_i^T-CARB_i^0=(7)+(8)+(9)+(10)+(11)+(12) \tag{6}$$

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[2] For the national calculation, GDP was used instead.

[3] The urban population and the rural population were distinguished according to the definitions in the statistical databases (see section 3.2 for the data sources). The floating population was not considered in this study, because the data for it were unavailable in the statistical databases. Instead, we used the data on the urban resident population in the statistical databases to measure urbanization.

Carbon intensity effect:

$$\Delta CARB^{T}_{C\_\text{int},i} = \frac{CARB_i^T - CARB_i^0}{\ln CARB_i^T - \ln CARB_i^0} \times \ln \frac{C\_\text{int}_i^T}{C\_\text{int}_i^0} \tag{7}$$

Energy intensity effect:

$$\Delta CARB^{T}_{E\_\text{int},i} = \frac{CARB_i^T - CARB_i^0}{\ln CARB_i^T - \ln CARB_i^0} \times \ln \frac{E\_\text{int}_i^T}{E\_\text{int}_i^0} \tag{8}$$

Consumption inhibition effect:

$$\Delta CARB^{T}_{C\_\text{inb},i} = \frac{CARB_i^T - CARB_i^0}{\ln CARB_i^T - \ln CARB_i^0} \times \ln \frac{C\_inb_i^T}{C\_inb_i^0} \tag{9}$$

Resident consumption effect:

$$\Delta CARB^{T}_{R\_con,i} = \frac{CARB_i^T - CARB_i^0}{\ln CARB_i^T - \ln CARB_i^0} \times \left[ \begin{array}{l} S\_u_i^0 \ln \dfrac{P\_con\_u_i^T}{P\_con\_u_i^0} + \left(1 - S\_u_i^0\right) \ln \dfrac{P\_con\_r_i^T}{P\_con\_r_i^0} \\ + S\_u_i^0 \ln \dfrac{PC\_con\_u_i^T}{PC\_con\_u_i^0} + \left(1 - S\_u_i^0\right) \ln \dfrac{PC\_con\_r_i^T}{PC\_con\_r_i^0} \end{array} \right] \tag{10}$$

Population urbanization effect:

$$\Delta CARB^{T}_{P\_urb,i} = \frac{CARB_i^T - CARB_i^0}{\ln CARB_i^T - \ln CARB_i^0} \times \left[ S\_u_i^0 \ln \frac{P\_pop\_u_i^T}{P\_pop\_u_i^0} + \left(1 - S\_u_i^0\right) \ln \frac{P\_pop\_r_i^T}{P\_pop\_r_i^0} \right] \tag{11}$$

Population size effect:

$$\Delta CARB^{T}_{POP,i} = \frac{CARB_i^T - CARB_i^0}{\ln CARB_i^T - \ln CARB_i^0} \times \ln \frac{POP_i^T}{POP_i^0} \tag{12}$$

$\Delta CARB_X$ shows six factors ($X$) entailed in the decomposition analysis. The superscripts 0 and $T$ in the above equations denote the base year (1990) and the calculation period, respectively. $S\_u_i{}^0$ was applied instead of $S\_u_i{}^T$ to calculate the effects of resident consumption and of population urbanization (eqs.(10) and (11)). To perform the calculations of the differences between two periods, $S\_u_i$ was actually based on the point elasticity value during period 0, and the change in adjacent years was negligible (Zhu and Wei, 2013).

### 3.2. Data

The relevant data during 1990–2016 (i.e., *ENE*, *GRP*, *RES_u*, *RES_r*, *POP_u*, and *POP_r*) were extracted from the official provincial statistical yearbooks (see Table A2 for the data sources). The national-level data were extracted from the China Statistical Yearbook (National Bureau of Statistics of China, 2017).

The statistical yearbooks do not include $CO_2$ emissions data; we therefore calculated the amount of $CO_2$ emissions per province using energy consumption data extracted from statistical yearbooks as follows (Intergovernmetal Panel on Climate Change, 2006):

$$CARB_i = \sum CARBij = \sum FUEL_{ij} \times SC_j \times SEC_j \times \frac{44}{12} \tag{13}$$

where *FUEL* denotes the energy consumption, *SC* denotes the conversion coefficient of standard coal for different energy types, *SEC* denotes the carbon emission coefficient, and *j* represents the different types of fossil fuels. Table A1 shows the corresponding values of *SC* and *SEC* by energy type.

## 4. Results and discussion

In this section, we first discuss the national-level results of decomposition analysis and subsequently provide a detailed analysis of provincial-level data.

### 4.1. Drivers of changes in $CO_2$ emissions under urbanization at the national level

Fig. 2 shows the results of a decomposition analysis of national-level data for China. The overall trend is that China's $CO_2$ emissions show an upward trend by 2013, and the emissions accelerate after 2000. Generally, the energy intensity effect has a strong restraining effect on $CO_2$ emissions. Since the launch of the 11th Five-Year Plan (2006–2010), the Chinese government introduced a policy of energy conservation and emission reduction, which significantly improved energy efficiency. As a result, the energy intensity effect, which was relatively stable until 2005, was magnified from around 2005 and, finally, became the most important factor driving the reduction in $CO_2$ emissions.

Another factor contributing to the reduction of $CO_2$ emissions is the carbon intensity effect. Compared with the diversified and clean energy structure in developed countries, China's energy consumption remains highly dependent on high-carbon fuels. Therefore, the carbon intensity effect is relatively weak in China. Nevertheless, a trend of gradual enhancement of the carbon intensity effect appears after 2010. This is because the Chinese government began promoting an optimized energy structure during the 12th Five-Year Plan while regulating the growth of high-carbon energy sources and encouraging diversified energy development.

As shown in Fig. 2, the continuous growth of $CO_2$ emissions is mainly caused by the positive resident consumption effect. The urban population continuously grows and simultaneously drives the increase in urban consumption. Currently, the population urbanization effect and the consumption inhibition effect are positive influences on the growth of China's $CO_2$ emissions. However, from around 2013, these two effects have gradually weakened. The effect of consumption inhibition reflects the degree of economic restraint on resident consumption as described by eq. (2). During the period 1990–2010, the proportion of resident (or household) consumption in GDP decreased significantly, from 49.5% to 35.6% (National Bureau of Statistics of China, 2017). However, in the same period, the proportion of government expenditure in GDP remained stable, whereas those of investment and net export increased. As a result, the positive impact of the consumption inhibition effect has been increasing, as the figure shows. During the period 2010–2016, however, the proportion of resident consumption rose from 35.6% to 39.2%. At the same time, whereas the proportions of government expenditure and investment in GDP remained stable, that of net export decreased. Consequently, the positive impact of the consumption inhibition effect has been declining since 2011. During the 12th Five-Year Plan, a strategic national policy has entailed expanding domestic demand, with the government gradually relinquishing its macro control of the economy. This strategy, in turn, has promoted a decrease in the positive consumption inhibition effect on $CO_2$ emissions. Furthermore, in 2014, the new national urbanization plan aimed to transform the urbanization mode into sustainable development was officially released, resulting in the gradual weakening of the positive effect of population urbanization on $CO_2$ emissions.

### 4.2. Drivers of changes in $CO_2$ emissions under urbanization at the provincial level

#### 4.2.1. Overall provincial trend relating to the six factors

Variations in population distribution, energy structures, and economic development in China are clearly discernible and linked to natural geographical conditions. Therefore, regional differences should be

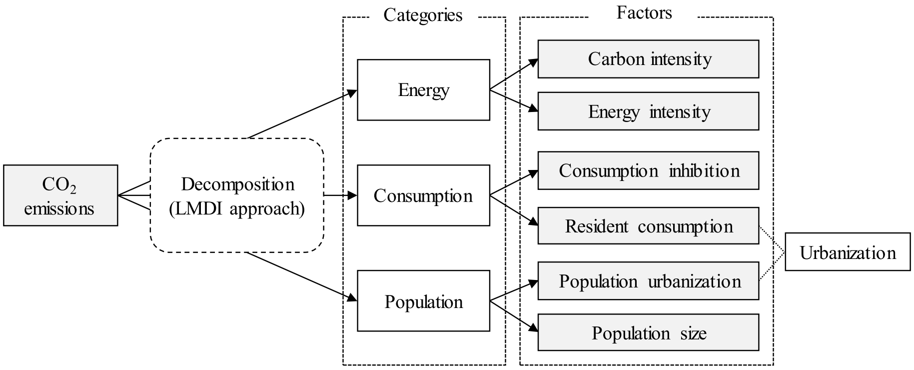

**Fig. 1.** Structure of the decomposition analysis. Note: The factors shaded in gray were used for the decomposition calculation.

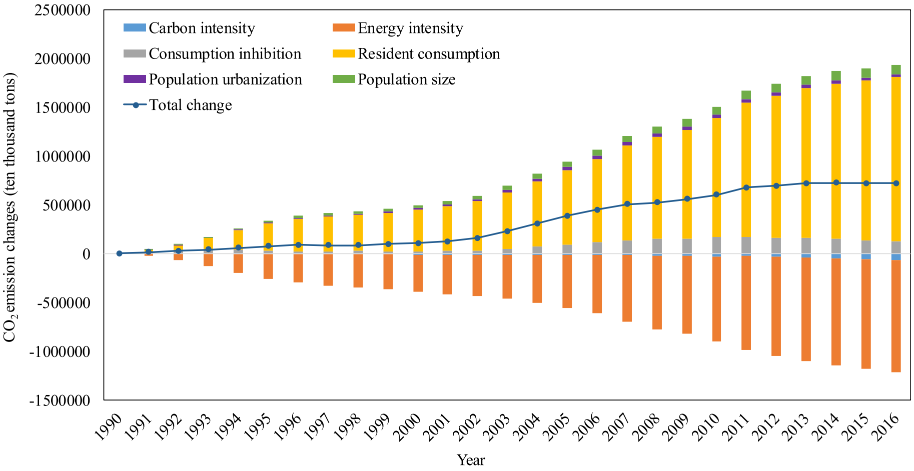

**Fig. 2.** National-level results of the decomposition analysis. Emissions for each year are relative to those in 1990.

considered in an analysis of the factors influencing $CO_2$ emissions in China. Moreover, we attempted to elucidate similarities and differences in results at the national and provincial levels, thereby addressing the shortcomings of previous studies that used national-level data, which may yield above-average results. Fig. 3 shows the results of the provincial-level analysis.[4]

Generally, while the $CO_2$ emissions in all the provinces increased over time, the changes in $CO_2$ emissions exhibited a specific distribution pattern. The $CO_2$ emissions are evidently concentrated in China's four key industrial bases (Central and Southern Liaoning, Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta). In addition, the $CO_2$ emissions are also grouped in China's coal-rich regions, notably, Shanxi, Shaanxi, Inner Mongolia, and Xinjiang in the north and Guizhou in the south. The established coal reserves in these five provinces account for about 80% of China's total coal reserves; meanwhile, the energy sector in these provinces is one of the important forces for economic development.

Fig. 3c, e, and g reveal that the distributions of energy intensity, resident consumption, and the population size effects exhibit similar patterns, being mostly concentrated in China's industrial bases and the major energy-producing provinces. On the one hand, urbanization progress is more rapid in the economically developed regions than in the other regions, which could encourage innovations relating to production technology and promote population aggregation. On the other hand, advanced economic development continuously enhances resident consumption power, contributing to the accelerated growth of $CO_2$ emissions.

A comparison of carbon intensity effects at the national and provincial levels (Figs. 2 and 3b) revealed some differences. At the national level, the carbon intensity effect has had a negative impact on $CO_2$ emissions since 1993. However, as Fig. 3b shows, some provinces still have a positive carbon intensity effect, particularly in the northern areas, such as Inner Mongolia and Gansu, which are rich in coal resources while the comprehensive economic strength is poor. Consequently, their development has heavily relied on coal, resulting in a positive carbon intensity effect.

The consumption inhibition effect was found to be positive in most provinces (Fig. 3d), whereas it was negative in the economically developed regions, such as Shanghai and Beijing. Since China's reform and opening-up policy, Shanghai has attracted further foreign investments. With the economy entering a high stage, Shanghai's urbanization mode has added the concept of sustainable development, which aims to change the driving force of the economy from an investment-centered mode to a domestic demand-led economic growth mode. Liaoning and Shanxi also demonstrated a negative consumption inhibition effect. However, based on the urbanization mode, they differ from Beijing and Shanghai. As typical resource-based provinces, the urbanization development of Liaoning and Shanxi was over-reliant on energy and government intervention. With the resource-based urban development crisis, these two provinces began to carry out industrial transformation and upgraded, aiming at expanding the consumption capacity of urban residents to drive economic growth.

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[4] All the time-series for the provincial decomposition results are shown in Fig. A2.

A great difference in the national- and provincial-level results in the decomposition analysis can be observed relating to the population urbanization effect (Figs. 2 and 3f). This effect ultimately did not have a negative impact on $CO_2$ emissions at the national level, while the provincial distribution of negative population urbanization effect was mostly concentrated in southern China, especially in the Yangtze River Delta (Fig. 3f). Most of these provinces are economically developed. In addition, the decomposition results reveal that the change in the population urbanization effect approximated an inverse u-shape (Fig. A2).

#### 4.2.2. Impacts of energy and technology on changes in $CO_2$ emissions

A case study by Sichuan and Inner Mongolia illustrates the impact of regional energy and technology on $CO_2$ emissions. Sichuan is one of the representative regions with a mature development of clean energy technology in China; meanwhile, it also has the second largest source of hydropower in China. Inner Mongolia in the northern part of China is one of the main domestic producers of coal resources. Fig. 4 shows the decomposition results and energy structures in Sichuan and Inner Mongolia.

The decomposition results for Sichuan (Fig. 4a) show that the negative carbon intensity effect and the energy intensity effect have increased over time and are the main forces restraining $CO_2$ emissions. In contrast, the carbon intensity effect evidences frequent changes, and it generally remains negative. Moreover, from 2011 onward, the negative carbon intensity effect significantly increased. The likely reason for this increase is that the Sichuan government set goals of developing clean and renewable energy and reducing the proportion of high-carbon fuels in its 12th Five-Year Plan. Starting from 2006, energy intensity has significantly improved. The transformation of traditional agriculture into modern agriculture and the rapid development of tertiary industry are two key reasons for this improvement.

In the case of Inner Mongolia, the carbon intensity effect was significantly positive. Differing from Sichuan, the energy intensity effect in this province entailed only a negative impact on $CO_2$ emissions (Fig. 4b). Coal accounts for a high proportion of energy consumption in Inner Mongolia, and the proportion shows a rising trend. Meanwhile, the penetration of clean energy has occurred at a very slow pace. Therefore, the strongly positive carbon intensity effect in Inner Mongolia is mainly attributable to its coal-dependent energy structure. From 2013 onward, the energy intensity effect has been stable. During the 12th Five-Year Plan, the Inner Mongolian government promoted the transformation of the industrial structure from being resource based to being non-resource based. The transformation and upgrading of industrial structure caused the reduction of energy consumption since 2012, which weakened the negative effect of energy intensity.

#### 4.2.3. Effects of consumption inhibition on changes in $CO_2$ emissions under different economic models

The consumption inhibition effect is closely related to the economic model. The results of provincial-level data (Fig. 3d) show a negative consumption inhibition effect in most economically developed regions. However, in developing regions, because the economic driving force of investments exceeded that of consumption, the impact of the consumption inhibition effect on $CO_2$ emissions is positive. In addition, during years with relatively high investment rates, $CO_2$ emissions tend to increase. Here we choose Beijing, Shanxi, and Henan as case studies to compare the different reasons for the change in the consumption inhibition effect. Beijing and Shanxi are two typical provinces where the reasons for the negative consumption inhibition effect on $CO_2$ emissions are different. In contrast, Henan, which is a traditional agricultural province with a slow-paced urbanization process, shows an obviously positive consumption inhibition effect on $CO_2$ emissions.

The consumption inhibition effect is substantially affected by the adopted model of economic development. China's reform and opening-up policy, implemented in the late 20th century, enabled rapid economic development throughout the country. Beijing's investment rate peaked at 68.8% in 1994 (Fig. 5d), and the development of production and the market was unprecedented. During the same period, the positive effect of consumption inhibition also accelerated (Fig. 5a). However, in 1995, macro control entered the soft-landing stage, and the investment rate decreased annually. Expanding domestic demand first appeared in planning content under the 11th Five-Year Plan, leading, in 2007, to a situation in which Beijing's consumption rate exceeded its investment rate. During the 12th Five-Year Plan, there was a greater focus on expanding Beijing's domestic demand and stimulating consumption to promote more stable and sustainable economic development. The adoption of the new economic development model eventually resulted in a negative consumption inhibition effect.

The negative impact of Shanxi's consumption inhibition effect on $CO_2$ emissions appeared around 2015, which is later than that in Beijing (Fig. 5b). From 1990 to 2000, the depression of coal prices led to a decrease in investments in coal production. For a while, the $CO_2$ emission increases were relatively small. They have even had a negative growth since 1996. With the implementation of the Rise of Central China Policy, the capital formation rate of Shanxi had been continuously growing since 2001 and reached its peak in 2013 (Fig. 5e). In addition, $CO_2$ emissions also had been growing rapidly in the same period. During the 12th Five-Year Plan, Shanxi further promoted the transformation from a resource-based economy to a demand-led economy, aiming to expand the consumption capacity of urban residents. As a result, around 2012, the resident consumption rate began to rapidly increase accompanied by the reduction of $CO_2$ emissions, which eventually promoted the consumption inhibition effect to turn into a negative impact on $CO_2$ emissions.

By contrast, Henan experienced a positive consumption inhibition effect during the study period (Fig. 5c). At the onset of the 21st century, national economic policies, such as the Rise of Central China Policy, enabled Henan's economy to gradually progress, finally entering a stage of accelerated development. The steady increase in the proportion of secondary industries resulted in a rapid rise in Henan's $CO_2$ emissions at the beginning of the 21st century, and around 2005, the capital formation rate rose above the final consumption rate (Fig. 5f). Supported by national preferential policies, Henan succeeded in attracting many industries that shifted from eastern coastal areas and acquired more developed production technology from industrial transfers. Notably, starting around 2010, the growth of $CO_2$ emissions slowed down while the economy developed.

#### 4.2.4. Population urbanization effect and regional development models

Most provinces with negative population urbanization effects are concentrated in the south, especially in the Yangtze River Delta. One of these provinces, Jiangsu, is an important Chinese province in terms of its advanced economy and urbanization. Liaoning, by comparison, is an important base for petroleum production with relatively slow urbanization in northern China. In addition, the trends for population urbanization effect exhibited an inverse u-shape (Fig. 6c and d).

During 1990–2000, the positive population urbanization effect in Jiangsu continuously increased in line with the acceleration of the urbanization process (Fig. 6c and e). The development and opening up of the Shanghai Pudong area that borders on Jiangsu has provided an opportunity for the overall development of Jiangsu's export-oriented economy, which is the main driver of Jiangsu's urbanization. The level of urbanization increased at a fast pace from 27.3% to 41.5% from 1996 to 2000. During the 11th Five-Year Plan, Jiangsu modified the industrial structure and developed a high-tech industry to provide a new impetus for the advancement of urbanization. Since 2000, as a result of the adjustments made to the mode of urbanization, the positive impact of the population urbanization effect on $CO_2$ emissions gradually decreased and was eventually transformed into a negative effect in 2004.

Although Liaoning has a high level of urbanization, the growth rate of urbanization there is relatively slow (Fig. 6f). Because Liaoning is one

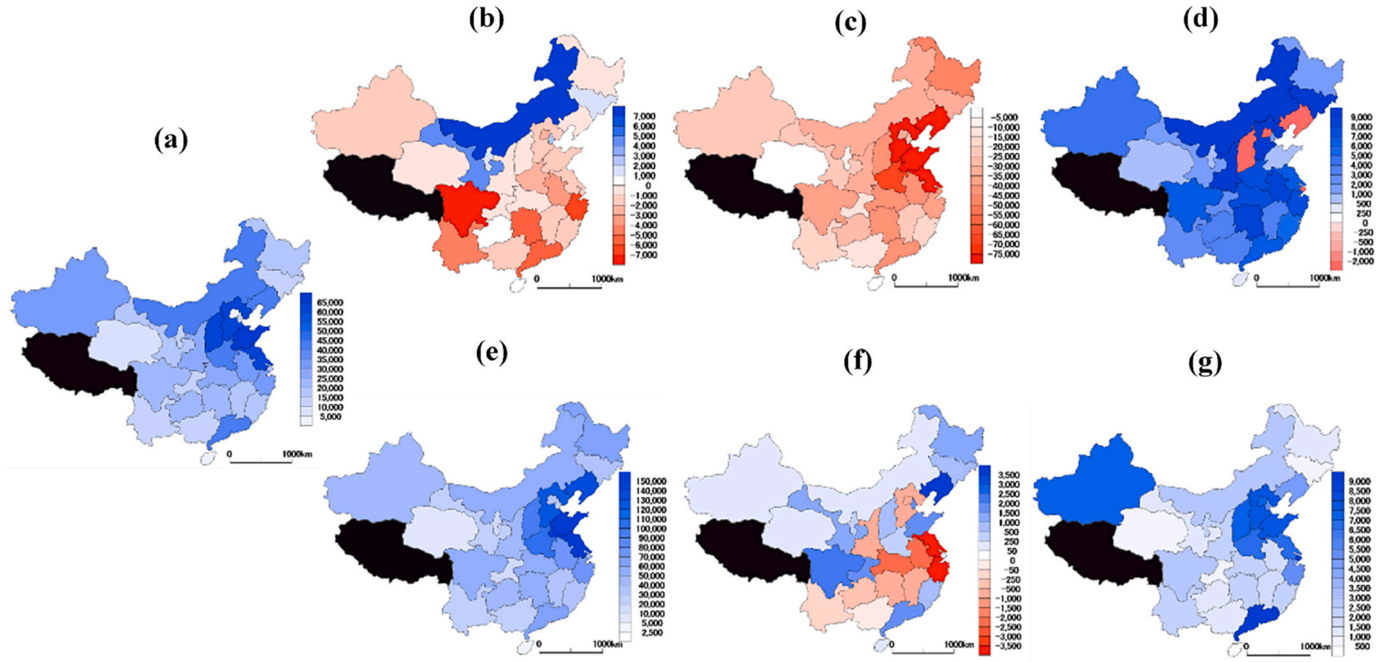


**Fig. 3.** (a) Changes in total $CO_2$ emissions and the impacts of six factors on $CO_2$ emissions by province: (b) the carbon intensity effect, (c) the energy intensity effect, (d) the consumption inhibition effect, (e) the resident consumption effect, (f) the population urbanization effect, and (g) the population size effect during 1990–2016 (unit: 1,000 tons of $CO_2$ emissions). The Tibet Autonomous Region, shaded black, was excluded from our study because of a lack of available data. The maps show only mainland China.

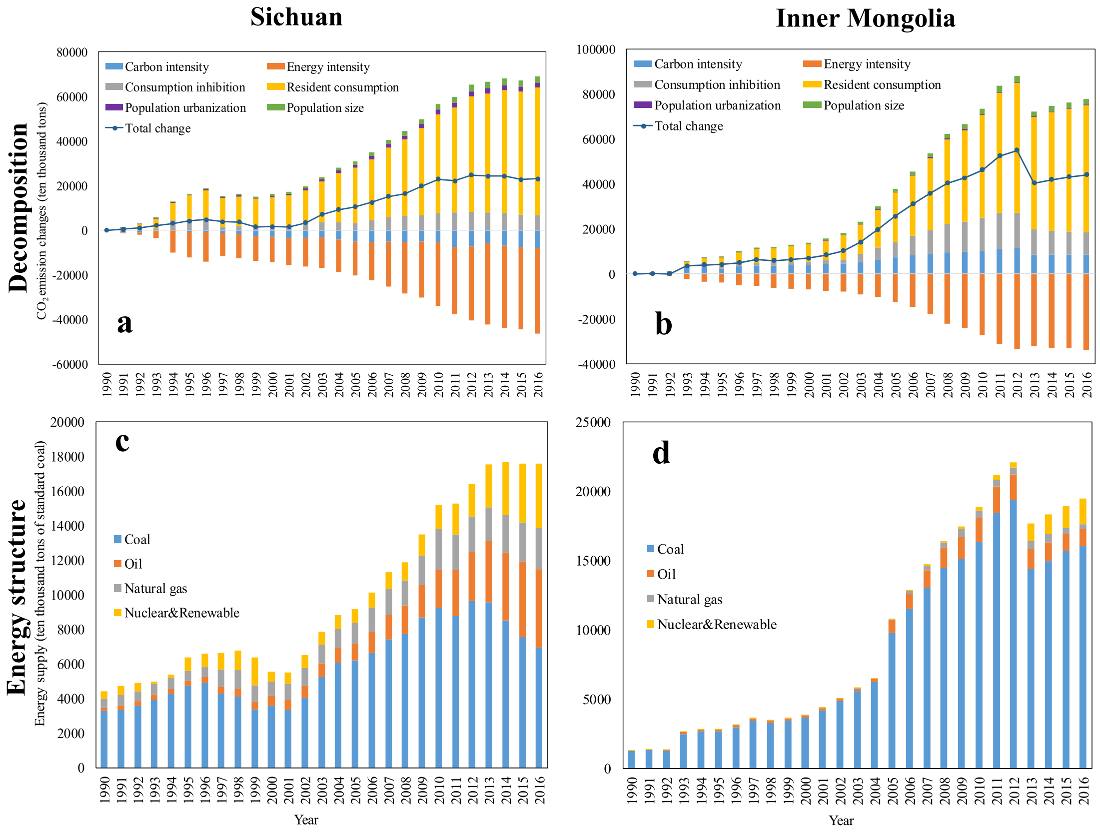


**Fig. 4.** Decomposition results for Sichuan and Inner Mongolia (a and b) and their structures of energy supply (c and d).

of the important old industrial bases in China, its rapid industrialization has been the most important driving force for urbanization, resulting in a relatively high degree of urbanization in the province. In 1990–2000, the reform of the state-owned assets-supervision system in an agglomeration of heavy-industry cities led to a deceleration of urbanization, which led in turn to a slow increase in the positive impact of the population urbanization effect (Fig. 6d). During the 10th Five-Year Plan (2001–2005), Liaoning, where urban agglomeration centered on the middle and southern regions, promoted the expansion of urbanization in the adjacent regions, resulting in the explosive growth of urbanization. As a result, the positive impact of the population urbanization effect has increased significantly since 2000. After 2005, the energy bottleneck of Liaoning's energy-dependent economy increased in severity, and the ability of heavy industry to absorb the labor force continuously decreased, which led to a slowdown in the growth of the population urbanization effect. During the 12th Five-Year Plan, Liaoning implemented the new urbanization policy, which was designed to improve the industrial structure, expand the service industry, and promote the transformation of energy-intensive industry into technology-intensive industry. Consequently, the population urbanization effect began to decline after 2014.

### *4.2.5. Changes in the six factors from the perspective of urbanization*

In the previous discussions, we elucidated the differential impacts of six key drivers of China's $CO_2$ emissions by factor and province. Fig. 7 presents a summary of the impacts of changes relating to three broad categories (Fig. 1) and sheds further light on the effects of these drivers in the different provinces.

As shown in column (a) of Fig. 7, the effect of carbon intensity and energy intensity are the main drivers of $CO_2$ emission reduction. These two effects are also closely related to the energy structure and technology in the urbanization progress. An examination of the provinces with prominent carbon intensity effects reveals that their energy structures tend to be diversified and are not limited to a coal-centered structure. Energy technology has important effects on the urbanization progress that relate not only to energy consumption and energy efficiency but also to environmental impacts.

The population size effect is indicative of the progress of urbanization. Highly urbanized regions, such as Beijing and Shanghai, generate more employment opportunities, which encourage population aggregation, and industrial regions, such as Guangdong and Shandong, could also absorb large numbers of workers (column (c) of Fig. 7).

Among the six factors, the resident consumption effect is the main driver of carbon growth (column (b) of Fig. 7). This finding indicates that rapid urbanization within China is associated with a significant increase in residents' incomes and the overall strengthening of their consumption capacities. The positive effect is particularly apparent in key industrial bases, such as Shandong, Jiangsu. The consumption inhibition effect reflects the economic driving force of urbanization. The distribution of its negative effect, shown in column (b), suggests two distinct reasons. The first reason relates to highly developed urbanization, such as in Beijing. The second reason relates to the transformation of the economic model, such as in Shanxi.

At the national level, Zhu and Wei (2013) showed that resident consumption under urbanization is an important factor driving the increase of $CO_2$ emissions, while Wang et al. (2019a, b) found that urbanization and consumption patterns generally increase $CO_2$ emissions. Our study confirmed these findings that resident consumption has emerged as a vital new factor in the $CO_2$ emission growth under the progress of urbanization at the national level. However, at the provincial level, we also showed that these findings are not always true. For example, urbanization does not always increase $CO_2$ emissions. In some highly urbanized provinces, urbanization has shown an obvious restraining effect on $CO_2$ emissions.

At the provincial level, Zang et al. (2017) explored the effects of urbanization and household-related factors on residents' direct $CO_2$ emissions in Shanxi. However, our study comprehensively compared the effects of urbanization on $CO_2$ emissions and showed that the influencing factors differ by province.

## 5. Conclusions and policy recommendations

In this study, we applied a LMDI approach using six key drivers to examine the effects of urbanization on changes in $CO_2$ emissions across 30 Chinese provinces during 1990–2016. The main findings are as follows.

1) The impacts of urbanization on $CO_2$ emissions, which evidenced distinct regional characteristics, gradually increased during the study period.
2) The change in the population urbanization effect approximated an inverse u-shape, which evidently depends on the degree of urbanization. Moreover, most of the provinces evidencing a negative effect

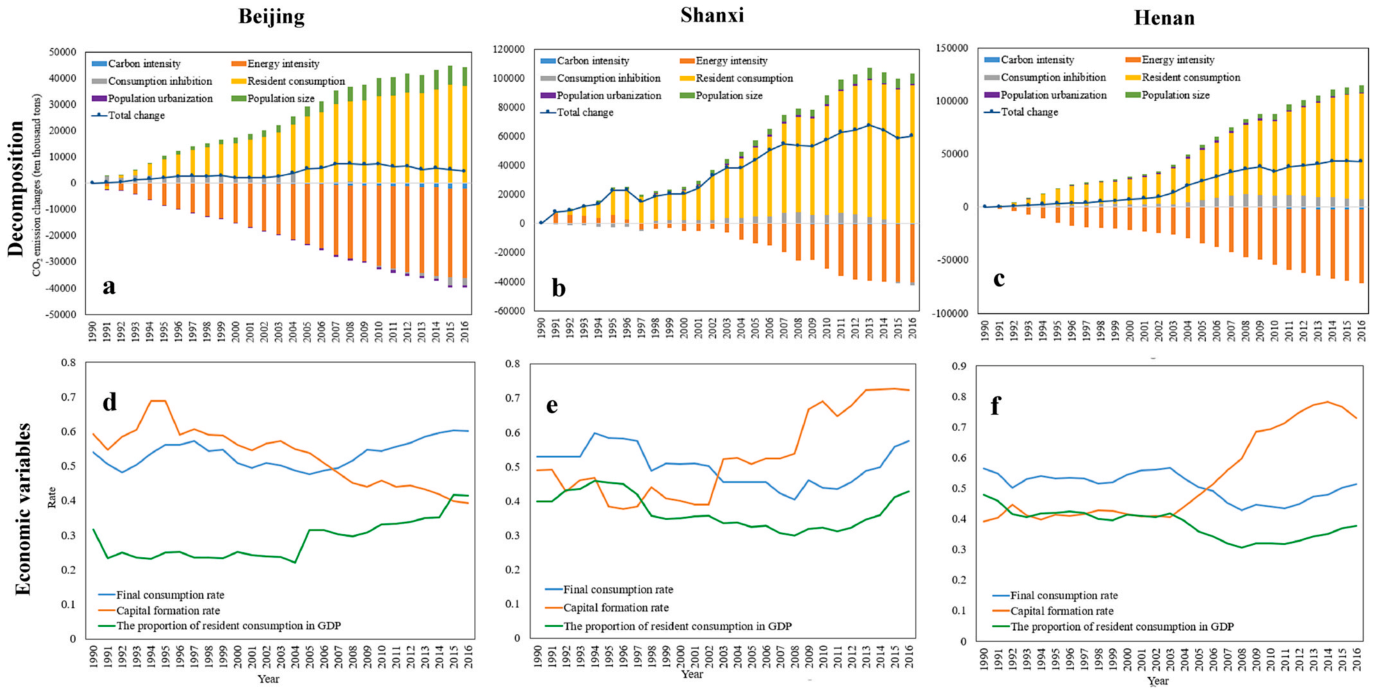


**Fig. 5.** Decomposition results for Beijing, Shanxi and Henan (a, b, and c) and their economic variables (d, e, and f).

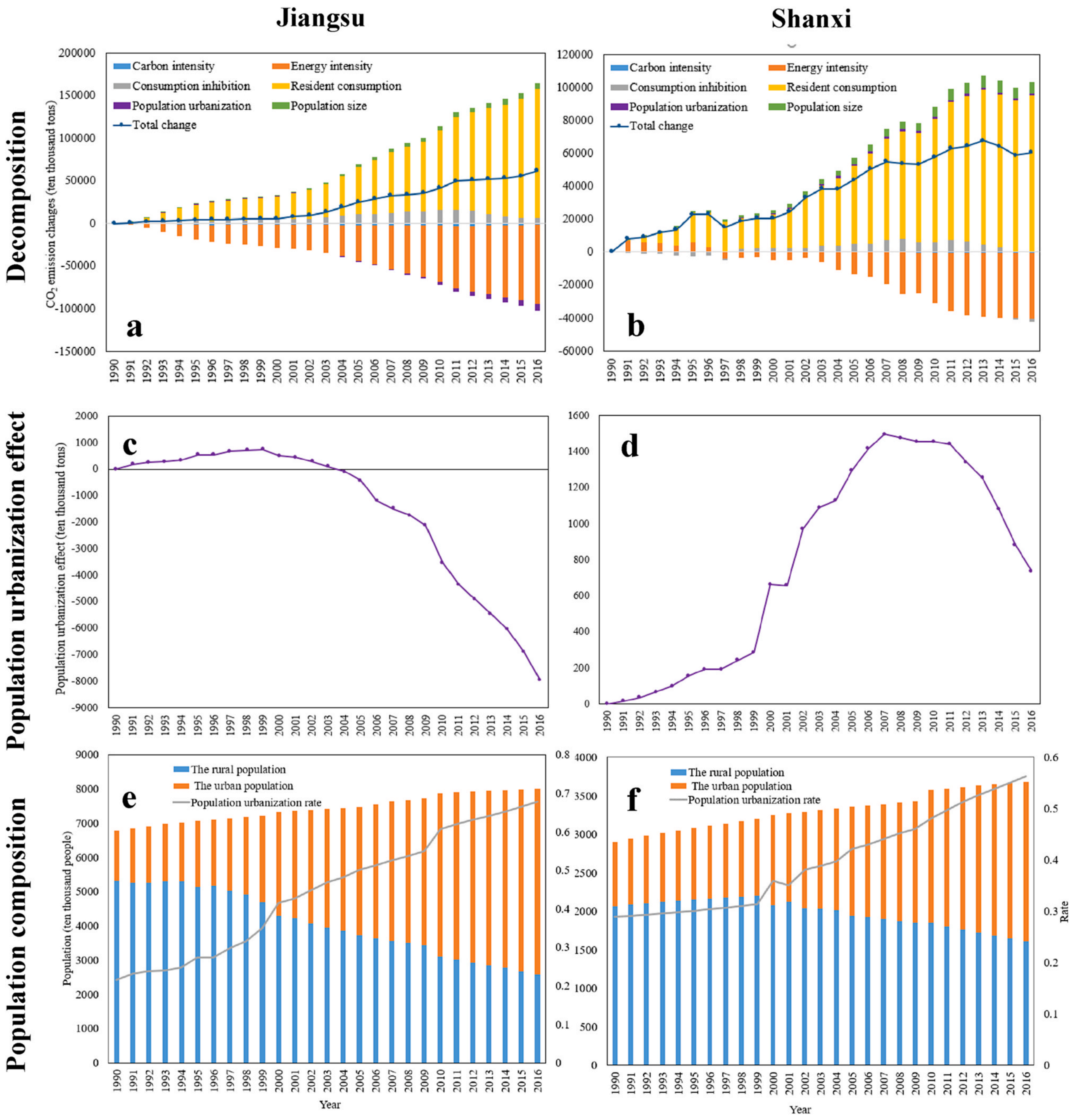
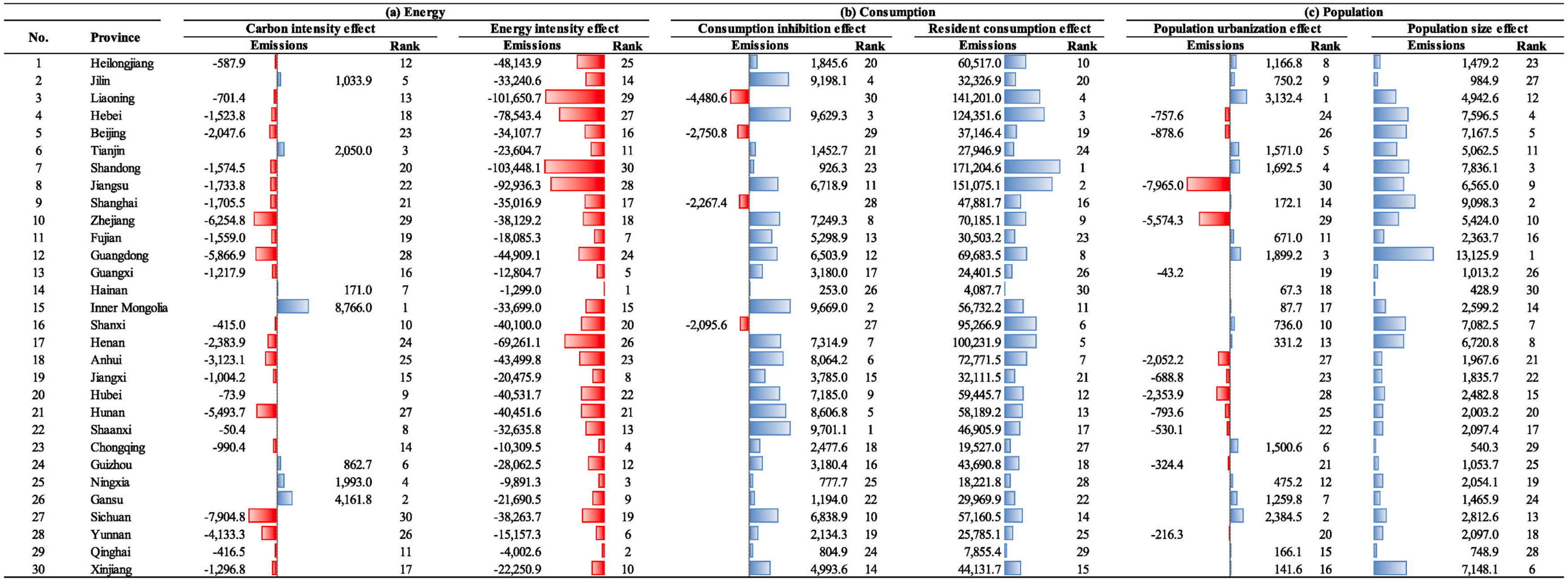


**Fig. 6.** Decomposition results for Jiangsu and Liaoning (a and b), their population urbanization effect (c and d), and their population composition (e and f).

were concentrated in the economically developed Yangtze River Delta.

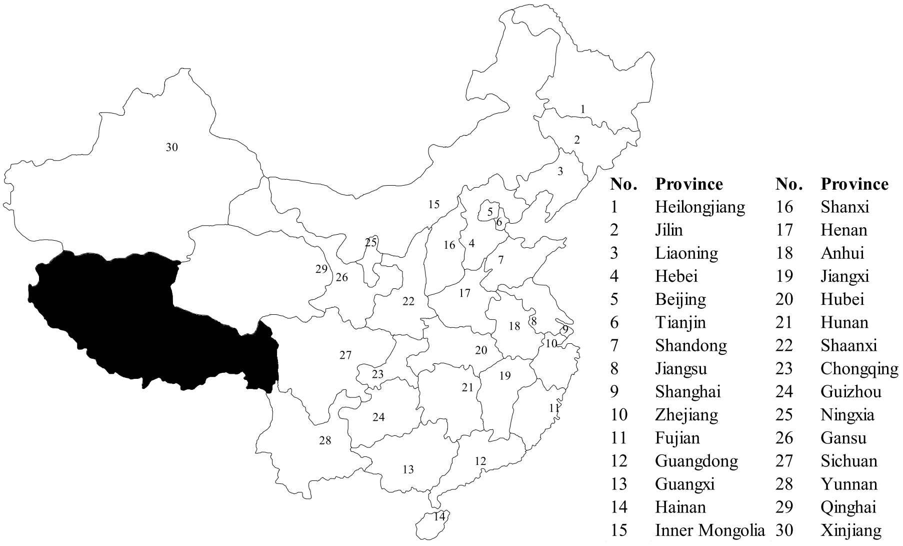
3) Carbon intensity evidenced a relatively weak effect on $CO_2$ emissions, and the energy intensity effect was the most important driver of reduced $CO_2$ emissions. The resident consumption effect was the main driver of increased $CO_2$ emissions in all the provinces.

In a period of low urbanization, production expansion is the reason that urbanization has a positive effect on $CO_2$ emissions. With the progress of urbanization, consumption has become a new driving factor in $CO_2$ emission growth, while urbanization shows a restraining effect on $CO_2$ emissions caused by the change in the urbanization mode. Specifically, the results of the analysis suggest the following policy recommendations:



| No. | Province | (a) Energy | | | | (b) Consumption | | | | (c) Population | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Carbon intensity effect | | Energy intensity effect | | Consumption inhibition effect | | Resident consumption effect | | Population urbanization effect | | Population size effect | |
| | | Emissions | Rank | Emissions | Rank | Emissions | Rank | Emissions | Rank | Emissions | Rank | Emissions | Rank |
| 1 | Heilongjiang | -587.9 | 12 | -48,143.9 | 25 | 1,845.6 | 20 | 60,517.0 | 10 | 1,166.8 | 8 | 1,479.2 | 23 |
| 2 | Jilin | 1,033.9 | 5 | -33,240.6 | 14 | 9,198.1 | 4 | 32,326.9 | 20 | 750.2 | 9 | 984.9 | 27 |
| 3 | Liaoning | -701.4 | 13 | -101,650.7 | 29 | -4,480.6 | 30 | 141,201.0 | 4 | 3,132.4 | 1 | 4,942.6 | 12 |
| 4 | Hebei | -1,523.8 | 18 | -78,543.4 | 27 | 9,629.3 | 3 | 124,351.6 | 3 | -757.6 | 24 | 7,596.5 | 4 |
| 5 | Beijing | -2,047.6 | 23 | -34,107.7 | 16 | -2,750.8 | 29 | 37,146.4 | 19 | -878.6 | 26 | 7,167.5 | 5 |
| 6 | Tianjin | 2,050.0 | 3 | -23,604.7 | 11 | 1,452.7 | 21 | 27,946.9 | 24 | 1,571.0 | 5 | 5,062.5 | 11 |
| 7 | Shandong | -1,574.5 | 20 | -103,448.1 | 30 | 926.3 | 23 | 171,204.6 | 1 | 1,692.5 | 4 | 7,836.1 | 3 |
| 8 | Jiangsu | -1,733.8 | 22 | -92,936.3 | 28 | 6,718.9 | 11 | 151,075.1 | 2 | -7,965.0 | 30 | 6,565.0 | 9 |
| 9 | Shanghai | -1,705.5 | 21 | -35,016.9 | 17 | -2,267.4 | 28 | 47,881.7 | 16 | 172.1 | 14 | 9,098.3 | 2 |
| 10 | Zhejiang | -6,254.8 | 29 | -38,129.2 | 18 | 7,249.3 | 8 | 70,185.1 | 9 | -5,574.3 | 29 | 5,424.0 | 10 |
| 11 | Fujian | -1,559.0 | 19 | -18,085.3 | 7 | 5,298.9 | 13 | 30,503.2 | 23 | 671.0 | 11 | 2,363.7 | 16 |
| 12 | Guangdong | -5,866.9 | 28 | -44,909.1 | 24 | 6,503.9 | 12 | 69,683.5 | 8 | 1,899.2 | 3 | 13,125.9 | 1 |
| 13 | Guangxi | -1,217.9 | 16 | -12,804.7 | 5 | 3,180.0 | 17 | 24,401.5 | 26 | -43.2 | 19 | 1,013.2 | 26 |
| 14 | Hainan | 171.0 | 7 | -1,299.0 | 1 | 253.0 | 26 | 4,087.7 | 30 | 67.3 | 18 | 428.9 | 30 |
| 15 | Inner Mongolia | 8,766.0 | 1 | -33,699.0 | 15 | 9,669.0 | 2 | 56,732.2 | 11 | 87.7 | 17 | 2,599.2 | 14 |
| 16 | Shanxi | -415.0 | 10 | -40,100.0 | 20 | -2,095.6 | 27 | 95,266.9 | 6 | 736.0 | 10 | 7,082.5 | 7 |
| 17 | Henan | -2,383.9 | 24 | -69,261.1 | 26 | 7,314.9 | 7 | 100,231.9 | 5 | 331.2 | 13 | 6,720.8 | 8 |
| 18 | Anhui | -3,123.1 | 25 | -43,499.8 | 23 | 8,064.2 | 6 | 72,771.5 | 7 | -2,052.2 | 27 | 1,967.6 | 21 |
| 19 | Jiangxi | -1,004.2 | 15 | -20,475.9 | 8 | 3,785.0 | 15 | 32,111.5 | 21 | -688.8 | 23 | 1,835.7 | 22 |
| 20 | Hubei | -73.9 | 9 | -40,531.7 | 22 | 7,185.0 | 9 | 59,445.7 | 12 | -2,353.9 | 28 | 2,482.8 | 15 |
| 21 | Hunan | -5,493.7 | 27 | -40,451.6 | 21 | 8,606.8 | 5 | 58,189.2 | 13 | -793.6 | 25 | 2,003.2 | 20 |
| 22 | Shaanxi | -50.4 | 8 | -32,635.8 | 13 | 9,701.1 | 1 | 46,905.9 | 17 | -530.1 | 22 | 2,097.4 | 17 |
| 23 | Chongqing | -990.4 | 14 | -10,309.5 | 4 | 2,477.6 | 18 | 19,527.0 | 27 | 1,500.6 | 6 | 540.3 | 29 |
| 24 | Guizhou | 862.7 | 6 | -28,062.5 | 12 | 3,180.4 | 16 | 43,690.8 | 18 | -324.4 | 21 | 1,053.7 | 25 |
| 25 | Ningxia | 1,993.0 | 4 | -9,891.3 | 3 | 777.7 | 25 | 18,221.8 | 28 | 475.2 | 12 | 2,054.1 | 19 |
| 26 | Gansu | 4,161.8 | 2 | -21,690.5 | 9 | 1,194.0 | 22 | 29,969.9 | 22 | 1,259.8 | 7 | 1,465.9 | 24 |
| 27 | Sichuan | -7,904.8 | 30 | -38,263.7 | 19 | 6,838.9 | 10 | 57,160.5 | 14 | 2,384.5 | 2 | 2,812.6 | 13 |
| 28 | Yunnan | -4,133.3 | 26 | -15,157.3 | 6 | 2,134.3 | 19 | 25,785.1 | 25 | -216.3 | 20 | 2,097.0 | 18 |
| 29 | Qinghai | -416.5 | 11 | -4,002.6 | 2 | 804.9 | 24 | 7,855.4 | 29 | 166.1 | 15 | 748.9 | 28 |
| 30 | Xinjiang | -1,296.8 | 17 | -22,250.9 | 10 | 4,993.6 | 14 | 44,131.7 | 15 | 141.6 | 16 | 7,148.1 | 6 |

**Fig. 7.** Contributions of energy, consumption, and population to energy-related $CO_2$ emissions in 2016 (relative to 1990).
Note: The blue-colored (red-colored) bars show increases (decreases) in $CO_2$ emission.



| No. | Province | No. | Province |
|---|---|---|---|
| 1 | Heilongjiang | 16 | Shanxi |
| 2 | Jilin | 17 | Henan |
| 3 | Liaoning | 18 | Anhui |
| 4 | Hebei | 19 | Jiangxi |
| 5 | Beijing | 20 | Hubei |
| 6 | Tianjin | 21 | Hunan |
| 7 | Shandong | 22 | Shaanxi |
| 8 | Jiangsu | 23 | Chongqing |
| 9 | Shanghai | 24 | Guizhou |
| 10 | Zhejiang | 25 | Ningxia |
| 11 | Fujian | 26 | Gansu |
| 12 | Guangdong | 27 | Sichuan |
| 13 | Guangxi | 28 | Yunnan |
| 14 | Hainan | 29 | Qinghai |
| 15 | Inner Mongolia | 30 | Xinjiang |

**Fig. A1.** The geographical locations of 30 provinces in mainland China. The Tibet Autonomous Region, shaded black, was excluded from our study because of a lack of available data. This map shows only mainland China.

1) *Adjusting the energy structure based on regional resource characteristics*: The southwest regions, such as Sichuan and Yunnan, relying on abundant water and natural gas resources, should further expand the construction of clean energy infrastructure. As for the coastal regions, such as Zhejiang, they can rely on economic and technological advantages to adjust the power supply structure by developing photovoltaic, offshore wind power, nuclear power, and other renewable energy sources.
2) *Optimizing the economic development model*: For the economically developed provinces in the coastal areas, such as Jiangsu and Zhejiang, although the degree of urbanization is relatively high, they should further expand the pulling effect of consumption on the economy for the sake of sustainable and stable development. For the provinces in the four key industrial bases, it is important to actively promote the upgrading of the industrial structure to maintain the stable economic support for the development of urbanization. Furthermore, it is also necessary to expand the capacity of resident consumption to provide a more long-term impetus for urbanization.
3) *Formulating $CO_2$ emission reduction policies in accordance with local conditions of urbanization*: For the regions with low degrees of urbanization, such as Inner Mongolia and Gansu (in interior northwestern China), the progress of the urbanization largely depends on energy production (e.g., coal and crude oil), the carbon reduction measures should focus on adjusting the regional development mode. These regions should change the energy-dependent economy and promote the diversification of the industrial structure to provide a more stable driving force for urbanization. For regions with high degree of urbanization, such as the Yangtze River Delta, $CO_2$ emission reduction efforts should focus on deepening the connotation of sustainable development of urbanization and adjust the social consumption structure to reduce the pulling effect of consumption on $CO_2$ emissions.

Because the next extensive phase of urbanization will occur in developing countries, this study could provide inputs for developing countries seeking $CO_2$ emission reduction. In the process of developing their economies and accelerating urbanization, developing countries should consider the effect of urbanization on $CO_2$ emissions. This is because urbanization not only stimulates domestic demand but also increases $CO_2$ emissions caused by resident consumption. In addition, $CO_2$ emission reduction policies under the progress of urbanization in developing countries should conform to prevailing regional situations, accounting for their different characteristics, rather than being based solely on the overall characteristics of the country.

## Credit authorship contribution

**Yuzhuo Huang:** Conceptualization, Data curation, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Visualization. **Ken'ichi Matsumoto:** Conceptualization, Validation, Writing - review & editing, Supervision, Funding acquisition.

## Declaration of competing interest

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

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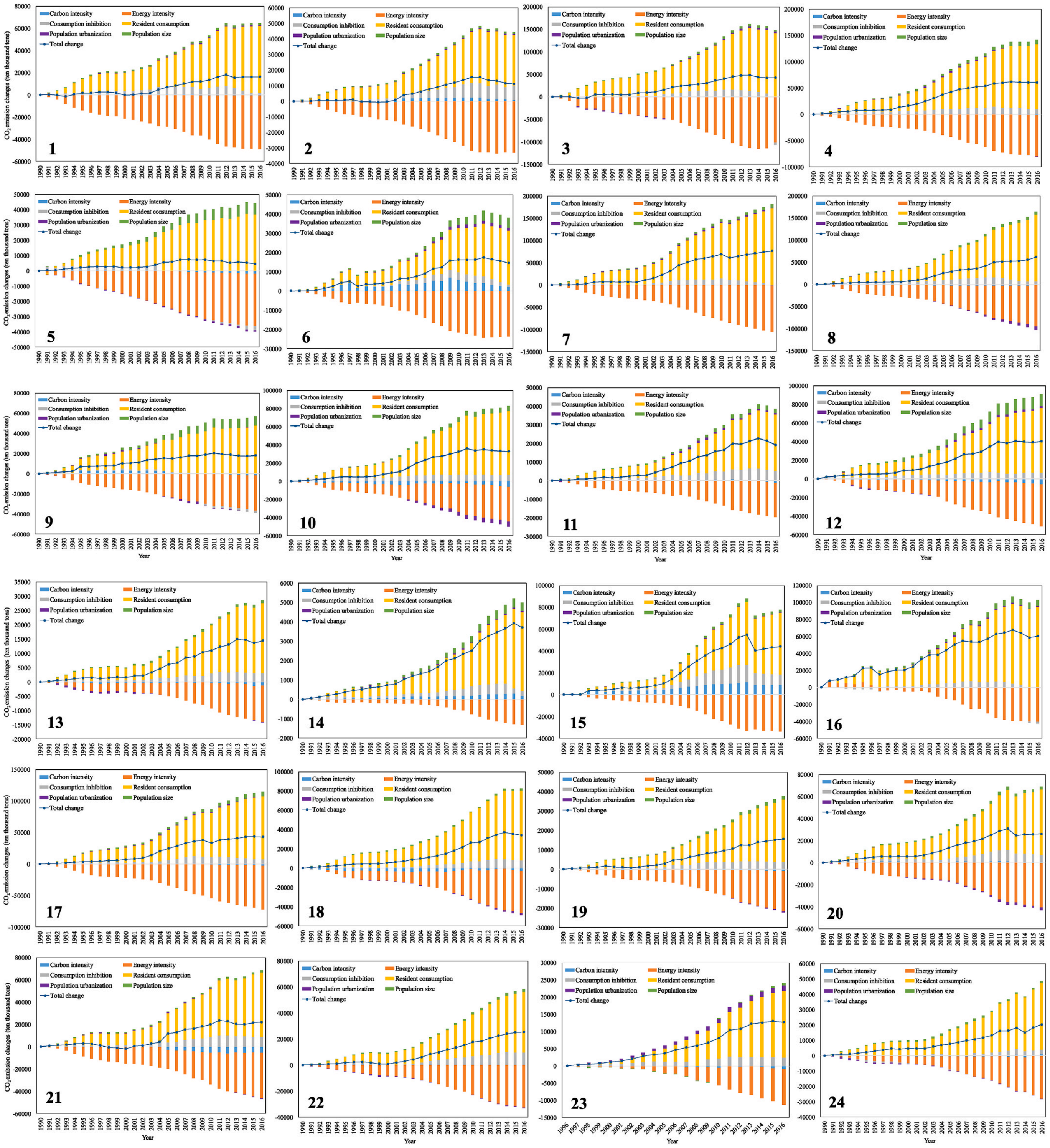

**Fig. A2.** Provincial-level decomposition results for all the years of study relative to 1990. The base year for Chongqing is 1996 because it became a directly administered municipality in 1997; hence, the data became available around that year. The panel numbers correspond to the numbers in Fig. A1.

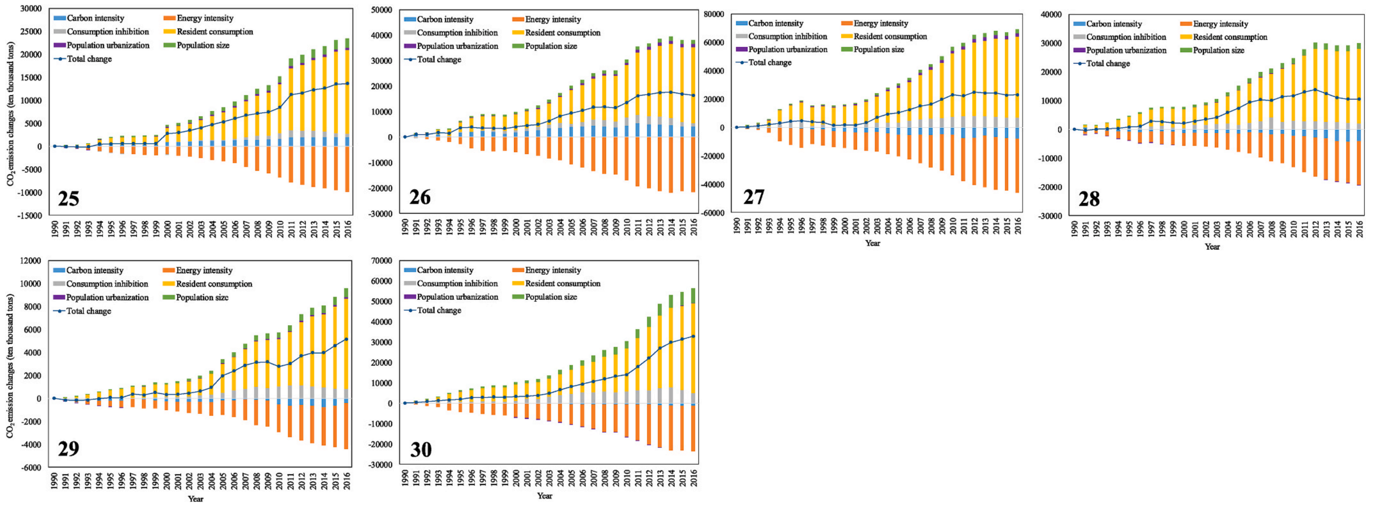

**Fig. A2.** (*continued*).

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.129000.

## Appendix

**Table A1**
Standard coal conversion and carbon emission coefficients

| Energy type | Standard coal conversion coefficient (ton of standard coal/ton of energy) | Carbon emission coefficient (ton of carbon/ton of standard coal) |
|---|---|---|
| Coal | 0.7143 | 0.7559 |
| Coke | 0.9714 | 0.855 |
| Crude oil | 1.4286 | 0.5857 |
| Fuel oil | 1.4286 | 0.6185 |
| Gasoline | 1.4714 | 0.5538 |
| Kerosene | 1.4714 | 0.5714 |
| Diesel | 1.4571 | 0.5921 |
| Natural gas | $1.33 \times 10^{-3}$ | 0.4483 |
| LPG | 1.7143 | 0.5042 |

Sources: National Bureau of Statistics of China, 2017 and Intergovernmental Panel on Climate Change (Intergovernmetal Panel on Climate Change, 2006).

**Table A2**
Sources of provincial-level data (as of March 3, 2021)

| No. | Province | URL |
|---|---|---|
| 1 | Heilongjiang | http://www.hlj.stats.gov.cn/tjsj/tjnj/ |
| 2 | Jilin | http://tjj.jl.gov.cn/tjsj/ |
| 3 | Liaoning | http://www.ln.stats.gov.cn/tjsj/sjcx/ndsj/ |
| 4 | Hebei | http://tjj.hebei.gov.cn/hetj/tjsj/jjnj/ |
| 5 | Beijing | http://tjj.beijing.gov.cn/tjsj/ |
| 6 | Tianjin | http://stats.tj.gov.cn/Category_29/Index.aspx |
| 7 | Shandong | http://www.stats-sd.gov.cn/col/col6279/index.html |
| 8 | Jiangsu | http://tj.jiangsu.gov.cn/col/col4009/index.html |
| 9 | Shanghai | http://www.stats-sh.gov.cn/html/sjfb/tjnj/ |
| 10 | Zhejiang | http://tjj.zj.gov.cn/col/col1525563/index.html |
| 11 | Fujian | http://tjj.fujian.gov.cn/xxgk/ndsj/ |
| 12 | Guangdong | http://www.gdstats.gov.cn/tjsj/gdtjnj/ |

(*continued on next page*)

**Table A2** (*continued*)

| No. | Province | URL |
|---|---|---|
| 13 | Guangxi | http://tjj.gxzf.gov.cn/tjsj/ |
| 14 | Hainan | http://stats.hainan.gov.cn/tjsu/ndsj/ |
| 15 | Inner Mongolia | http://tj.nmg.gov.cn/channel/nmg_tjj/col10471f.html |
| 16 | Shanxi | http://www.shanxi.gov.cn/sj/tjnj/ |
| 17 | Henan | http://www.ha.stats.gov.cn/sitesources/hntj/page_pc/tjfw/tjcbw/tjnj/list1.html |
| 18 | Anhui | http://tjj.ah.gov.cn/tjjweb/web/tjnj_view.jsp?_index = 1 |
| 19 | Jiangxi | http://www.jxstj.gov.cn/id_tjnj201803120104397238/column.shtml |
| 20 | Hubei | http://tjj.hubei.gov.cn/info/iIndex.jsp?cat_id = 10055 |
| 21 | Hunan | http://tjj.hunan.gov.cn/tjsj/tjnj/ |
| 22 | Shaanxi | http://tjj.shaanxi.gov.cn/site/1/html/126/127/233/list.htm |
| 23 | Chongqing | http://www.cqdata.gov.cn/publish.htm?code = A01 |
| 24 | Guizhou | http://stjj.guizhou.gov.cn/tjsj_35719/sjcx_35720/gztjnj_40112/ |
| 25 | Ningxia | http://nxdata.com.cn/publish.htm?cn = G01 |
| 26 | Gansu | http://www.gstj.gov.cn/HdApp/HdBas/HdClsContentMain.asp?ClassId = 70 |
| 27 | Sichuan | http://tjj.sc.gov.cn/tjcbw/tjnj/ |
| 28 | Yunnan | http://www.stats.yn.gov.cn/tjsj/tjnj/ |
| 29 | Qinghai | http://www.qhtjj.gov.cn/tjData/qhtjnj/http://tjj.hunan.gov.cn/tjsj/tjnj/ |
| 30 | Xinjiang | http://www.xjtj.gov.cn/tjfw/tjsj/ |

Note: All data were taken from the official websites of provincial governments.

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