# The consumption-based carbon emissions in the Jing-Jin-Ji urban agglomeration over China's economic transition

Bai, Yangchun; Zheng, Heran; Shan, Yuli; Meng, Jing; Li, Yuan

*DOI:*
10.1029/2021EF002132

AGU ADVANCING EARTH AND SPACE SCIENCE

Earth's Future

RESEARCH ARTICLE

10.1029/2021EF002132

# The Consumption-Based Carbon Emissions in the Jing-Jin-Ji Urban Agglomeration Over China's Economic Transition

**Yangchun Bai[1], Heran Zheng[2], Yuli Shan[3], Jing Meng[4], and Yuan Li[1]**

[1]Institute of Blue and Green Development, Shandong University, Weihai, China, [2]Industrial Ecology Programme, Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim, Norway, [3]Integrated Research for Energy, Environment and Society (IREES), Energy and Sustainability Research Institute Groningen University of Groningen, Groningen, Netherlands, [4]The Bartlett School of Sustainable Construction, University College London, London, UK

**Key Points:**

- The consumption-based emissions of Jing-Jin-Ji urban agglomeration and their driving forces behind were revealed
- Decreased emission intensity has contributed to emissions mitigation mostly during the economic transition period
- The consumption-based carbon emission distribution of 13 cities in Jing-Jin-Ji remained unchanged, which still lead by Beijing and Tianjin

**Supporting Information:**

Supporting Information may be found in the online version of this article.

**Correspondence to:**

Heran Zheng and Jing Meng,
heran.zheng@ntnu.no;
jing.j.meng@ucl.ac.uk

**Citation:**

Bai, Y., Zheng, H., Shan, Y., Meng, J., & Li, Y. (2021). The consumption-based carbon emissions in the Jing-Jin-Ji urban agglomeration over China's economic transition. *Earth's Future*, *9*, e2021EF002132. https://doi.org/10.1029/2021EF002132

Received 11 APR 2021
Accepted 21 JUL 2021

## Abstract

Since the 2008 financial crisis, China has been undergoing an economic transition consisting of prioritizing green economic and sustainable development instead of rapid growth driven by large-scale investment. However, there is still a lack of fine print on how subregional effort can contribute to national or full supply chain mitigation plans, especially downscaling to the city level. To bridge this knowledge gap, we selected Jing-Jin-Ji urban agglomeration, one of the economic centers but also featured by intensive emission for decades, to analyze the emission variance and driving forces from 2012 to 2015 as a case study. Based on the consumption accounting framework, the carbon emissions of Jing-Jin-Ji have decreased by 11.7 Mt $CO_2$ in total over the study period, and most cities showed the similar descending trend. The driving forces show that the emission intensity and production structure have largely reduced Jing-Jin-Ji's total due to measurements of economic transition. For instance, Beijing has decreased by 28.7 Mt of emission reduction which led by declined emission intensity. By contrast, per capita demands and growth of its population were the primary forces to increase emissions. To conclude, although the mitigation achievement is undeniable, we should also note that the economic transition has not changed the uneven pattern of selected urban agglomeration so far.

## Plain Language Summary

Jing-Jin-Ji urban agglomeration is one of the most key mitigation hotspots, where is home to 8% of the population and accounts for 10% of the national gross domestic product (GDP). With China entering a new economic development stage, Jing-Jin-Ji urban agglomeration has experienced economic transition, which refers to moving away from the heavy manufactory sector toward service industry and high value-added manufacturing. These supply reforms had an effect on consumption-based carbon emissions in the Jing-Jin-Ji urban agglomeration. Here, we focused on these effects and their driving factors due to economic transition. We found total consumption-based carbon emissions of Jing-Jin-Ji has decreased during 2012–2015. Most cities also showed the same declining trend, while Tianjin and less developed cities in Hebei province like Hengshui have increased consumption-based emissions. When looking into the driving forces, decreased emission intensity has contributed to emissions mitigation mostly. By contrast, both per capita demands and the growth of population induced more carbon emissions. In general, the economic transition benefited Jing-Jin-Ji carbon emissions mitigation, but the uneven pattern that consumption-based emissions lead by Beijing and Tianjin was not changed, and even could lead to more carbon emissions to undeveloped cities.

## 1. Introduction

After the 2008 financial crisis, China entered a new stage of economic transition, formulated as "the new normal," in which economic patterns shifted from rapid to lower growth but with a focus on higher quality (Mi et al., 2018; Zheng et al., 2020). The pattern of economic growth gradually shifted toward low investment and high consumption (Grubb et al., 2015), with a move away from heavy manufactory sector toward service industry and high value-added manufacturing (Green & Stern, 2015). In the new normal era, China prioritized environmental sustainability and a low carbon society, by developing clean energy and cleaning the energy mix (Zheng, Mi, et al., 2019; Zheng, Zhang, et al., 2019). This shift in economic growth patterns and the change in industrial structure curbed the growth of China's carbon emissions (Guan et al., 2018; Jackson et al., 2016). However, although measurements have been promoted in all the industrial sectors and on a national-wide scale, the fine print of subregional plans is still progressing slowly, as either emission variance or their driving forces behind are still not clear (Zhang, Bai, et al., 2021; Zhang, Yi, et al., 2021).

To make up this knowledge gap, varied attempts from regions (Zheng et al., 2020), prefectures (Z. Wang et al., 2018), or even cities (Feng et al., 2014) have been made to enrich the content of national-wide mitigation policies. With the increasing urbanization and booming urban population, cities are not only the home to half of the population but are also the primary carrier of production and consumption activities, and thus a major target of climate change mitigation efforts (Li et al., 2019). For example, the urbanization rate of China has increased from 36.22% to 59.6%, in the beginning two decades of the 20th century, and is predicted to reach 70% by 2030 (UNDP, 2013). In recent decades, a new characteristic of urbanization appeared, which is adjacent cities comprised urban agglomeration. In 2016, building 19 urban agglomerations have been proposed in the 13th 5-year plan in China (National Development and Reform Commission, 2016). Those urban clusters account for 29.1% of the territory but have 75.2% of population and 80.05% of GDP (Zheng et al., 2017). The high concentration of industry, large energy consumption, and rapid population growth have brought massive carbon emissions in those urban agglomerations, which brings a new challenge to achieve the 2060 net-zero target (Xinhuanet, 2020).

As one of China's largest urban agglomerations, Jing-Jin-Ji urban agglomeration, which includes Beijing, Tianjin, and 11 cities of Hebei Province (Figure S1), is home to 8% of the population and accounts for 10% of the national gross domestic product (GDP) (Zheng, Mi, et al., 2019; Zheng, Zhang, et al., 2019). With the economic development, Jing-Jin-Ji faces severe environmental problems, particularly in air pollution (Li et al., 2019), water scarcity (Zhao et al., 2017), and high greenhouse gas emissions (GHG) (Chen & Chen, 2019). In particular, carbon emission has more than tripled from 1997 to 2015 (Fan et al., 2019). Although several policies have been put into practice in emissions mitigation, most of them have little effect. One of the problems is the energy mix dominated by coal in Jing-Jin-Ji urban agglomeration for the long term. For example, Jing-Jin-Ji urban agglomeration consumed 370 million Tecs of coal, almost 5% of global coal consumption in 2012 (National Energy Administration, 2014). Despite the implementation of policies such as "using natural gas rather than coal," the proportion of clean energy consumption is still relatively low. Besides, cities in Hebei province, which encircles Beijing and Tianjin, make heavy industries such as iron and steel as pillar industry (W. Chen et al., 2017). Raw steel production in Hebei province reached 240 million tons in 2019, which more than double that of India (the world's second-largest raw steel producer) (World Steel Association, 2021). The single industrial organization makes it Hebei province hard to change industrial structure in a short term, which further aggravates the difficulties in regional emission mitigation. Furthermore, the economic development and distribution of industry in the urban agglomeration are hugely uneven. Beijing is dominated by the service sectors, while Tangshan and Handan in Hebei Province are known for their heavy manufactory (Zhang, Bai, et al., 2021; Zhang, Yi, et al., 2021). To undertake industrial relocation from Beijing, cities in Hebei province have undertaken a large number of heavy industries, which further exacerbates the uneven distribution of carbon emissions in Jing-Jin-Ji (Li et al., 2019). Now, after the financial crisis in 2008, Jing-Jin-Ji's GDP growth rate slowed down, shifting from high speed to medium-high speed, stepping into the "new normal ear" (which refers to a new pattern of economic development). The special economic development mode offers a turning point for emissions mitigation (Zheng, Mi, et al., 2019; Zheng, Zhang, et al., 2019). At the same time, a series of policies have been promulgated in Jing-Jin-Ji, one of the urgent tasks is to step up urban cooperation to decelerate $CO_2$ emissions (National Development and Reform Commission, 2015). However, the issue of what is carbon emissions patterns inside the Jing-Jin-Ji urban agglomeration and whether they have changed are still not clear, due to the data regarding city-level remains insufficient. Therefore, we notice the knowledge gap and keep watching on subregional carbon emissions patterns and their forces driving, which can help Jing-Jin-Ji getting out of hard emissions mitigation trouble.

A growing literature has sought to quantify carbon emissions in Jing-Jin-Ji (Zhang et al., 2019; Zheng et al., 2017). However, due to poor accessibility and timeliness of the city-level IO table, most scholars focused on single-year emissions patterns before 2012 and ignored the carbon emissions variation trend and its driving force (Zheng, Mi, et al., 2019; Zheng, Zhang, et al., 2019). In our study, we considered subregional geospatial in Jing-Jin-Ji urban agglomeration and revealed the resulting due to supply reforms introduced as part of the economic transition. Hence, first, an extended IO analysis model was used to account for the consumption-based $CO_2$ emissions of the 13 cities, describing the characteristics of the industry and the distinct role the 13 cities played. Second, this study illustrated the changes in transfer of hidden carbon emissions along supply chains in the urban agglomeration and identified the critical induced sectors and driving cities behind. Finally, using the structural decomposition analysis method (SDA), we further explored the main drivers of changes in carbon emissions in each city, as a result of economic transition. Special attention is paid to the effects of the new normal and the features of carbon emissions patterns in Jing-Jin-Ji. Here, we pay more attention to a subregional emissions pattern and explore the driving factors behind it, which enriches the city level emissions contents and conducive to making subregional emission mitigation goals. The detailed analysis reveals the carbon emissions characteristics from a consumption perspective and can also be used as a reference for researching other urban agglomerations within China and elsewhere.

## 2. Literature Review

Consumption-based accounting from the perspective of consumers redraws carbon emission responsibilities and can curb carbon emissions by controlling the flow of the supply chains, which better reflects the impact of human activities on global climate change (Barrett et al., 2013; Z.-M. Chen et al., 2018; Meng et al., 2017). There are numerous studies on consumption-based carbon emissions at the global and national levels (Zhang et al., 2020). For instance, Davis and Caldeira (2010)'s focused on global 113 countries and regions. Knight and Schor (2014) studied 29 high-income countries. National level consumption-based carbon emissions studies in the UK (Druckman & Jackson, 2009), the USA (Bin & Dowlatabadi, 2005), Australia (Steininger et al., 2018), and even in developing countries like India (Huang et al., 2021) and China (Wiedenhofer et al., 2017) were all shown by scholars. Within the last few years, studies in higher resolution geographic spatial like urban agglomeration, province, and city carbon emissions have been increased interest by scholars (Heinonen et al., 2020). For example, Hasegawa et al. (2015) analyzed prefectural carbon footprints in Japan for the first time. Heinonen and Junnila (2011) proposed a hybrid life cycle assessment (LCA) and calculated two metropolitan areas in Finland. Long and Yoshida (2018) used a city-level Input-Output model and paid attention to the center city of Japan- Tokyo. A major UK city, Bristol, was also studied by Millward-Hopkins et al. (2017). As for China, subnational consumption-based emissions inventory has also been establishing (Zhang et al., 2014). Feng et al. (2013) calculated consumption-based $CO_2$ emissions among Chinese provinces and found severe interprovincial carbon leakage. Shao et al. (2018) measured the consumption-based carbon emissions in 30 Chinese regions during 2007–2010. Mi et al. (2016) calculated the consumption-based $CO_2$ emissions of 13 representative Chinese cities and compared consumption-based with production-based emissions. Feng et al. (2014) focused on the consumption-based emissions of four Chinese megacities (Beijing, Shanghai, Tianjin, Chongqing), and found that consumption was responsible for a significant proportion of emissions to its territory and that it increased emissions in neighboring provinces through the supply chain. The detailed spatial scales of consumption-based emissions studies indicate that city could have a much greater impact on reducing $CO_2$ emissions.

In order to explore the drivers behind changes in carbon emission, the structure decomposition analysis (SDA) method is widely used by scholars, especially in energy consumption and carbon emissions studies (Seo et al., 2018; Su et al., 2013). When looking into China's $CO_2$ emissions, in early studies, some scholars explored the driving factors of emissions changes due to rapid economic development. For example, Guan et al. (2008) used the SDA model to explore the drivers behind the rapid increase in China's emissions from 1981 to 2002. They found changes in population and household consumption patterns contributed to increasing more emissions. Zhu et al. (2012) investigated changes in residential indirect emissions from 1992 to 2005 in China. The results revealed that carbon emission intensity was the most significant contributor to reducing carbon emissions. With China entering a new phase of economic development "new normal," there has been a shift of driving forces analysis from the impact of rapid economic development to the effect of economic transition. Mi et al. (2017) attached importance to determinants of China's carbon emission changes during 2005–2012. They found the largest restrain factors shifted from efficiency improved to structural optimized in the economic transition. From a Chinese export emissions perspective, Mi et al. (2017) revealed growth in export volume induced $CO_2$ increased, while changes in production structure and efficiency gains decreased after the global financial crisis. Zheng et al. (2020) divided China into eight regions and paid attention to regional heterogeneity of carbon emissions in the economic transition. They emphasized declined intensity and industrial structures reduced carbon emissions mostly. Zheng, Mi, et al. (2019) showed not only gains in energy efficiency reduced emission, but also deceleration of economic growth and changes in consumption patterns made large contributions in emission deceleration in the new phase of economic development. Most studies suggest the economic transition provides opportunities and can make large contributions to emissions mitigation.

A further look at Jing-Jin-Ji urban agglomeration study area, Zheng, Mi, et al. (2019) paid attention to water-carbon nexus issues, and revealed the inequality and imbalance of the Jing-Jin-Ji urban agglomeration. The indicated cities in Hebei province were energy suppliers and stayed at a disadvantage in carbon emissions mitigation. Mi et al. (2019) studied 11 cities in Hebei province, calculating and comparing their consumption-based emissions. They found more than half of emissions were embodied in imports and suggested that there was a need to strengthen interregional cooperation for carbon mitigation. Both of them accounted for single-year consumption-based emissions, which cannot reveal the emissions variations. Some scholars considered the temporal heterogeneity and explored its emission changes as well. But, most of them only focused on regional or provincial level. For instance, J. Chen et al. (2019) studied $CO_2$ emissions patterns in the Jing-Jing-Ji region from 2002 to 2012. Fan et al. (2019) used the same spatial scales and described driving factors from the regional levels. C. Wang et al. (2019) focused on the direct and indirect carbon emissions of residential consumption-based emissions in Beijing, Tianjin, and Hebei province. However, there is still a lack of city-level analysis in Jing-Jin-Ji emissions patterns as well as its emission variations driving factors, which this study addressed the issue.

## 3. Methods and Data Source

### 3.1. Consumption-Based Carbon Emission Accounting

To account for consumption-based emissions, first, we constructed the $CO_2$ emissions inventory according to reference (IPCC, 2006; Shan et al., 2017, 2019; Shan, Guan, Hubacek, et al., 2018; Shan, Guan, Zheng, et al., 2018). We then applied the EEIOA method to account for carbon emissions from consumption perspective.

American economist Wassily W. Leontief first proposed and founded the input-output model, which reveals the trade flow between different sectors through the supply chain (Leontief, 1986). With the multi-regional input-output (MRIO) table, the equation can be expressed as:

$$\mathbf{X} = \left(\mathbf{I} - \mathbf{A}\right)^{-1}\mathbf{F} \tag{1}$$

Using matrix representation, the technical coefficient matrix $\mathbf{A} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \cdots & \mathbf{A}^{1\mathbf{m}} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & & \mathbf{A}^{2\mathbf{m}} \\ \vdots & & \ddots & \vdots \\ \mathbf{A}^{\mathbf{n}1} & \mathbf{A}^{\mathbf{n}2} & \cdots & \mathbf{A}^{\mathbf{nm}} \end{bmatrix}$; $\mathbf{I}$ is the identity matrix, and $\left(\mathbf{I} - \mathbf{A}\right)^{-1}$ is the Leontief inverse matrix; The final demand $\mathbf{F} = \begin{bmatrix} \mathbf{F}^{11} & \mathbf{F}^{12} & \cdots & \mathbf{F}^{1\mathbf{m}} \\ \mathbf{F}^{21} & \mathbf{F}^{22} & & \mathbf{F}^{2\mathbf{m}} \\ \vdots & & \ddots & \vdots \\ \mathbf{F}^{\mathbf{n}1} & \mathbf{F}^{\mathbf{n}2} & \cdots & \mathbf{F}^{\mathbf{nm}} \end{bmatrix}$; The output, $\mathbf{X} = \begin{bmatrix} \mathbf{X}^{1} \\ \mathbf{X}^{2} \\ \vdots \\ \mathbf{X}^{\mathbf{m}} \end{bmatrix}$. Where $\mathbf{A}^{\mathbf{nm}} = [a_{ij}^{nm}]$, and $a_{ij}^{nm} = \frac{z_{ij}^{nm}}{x_j^m}$ is the technical coefficient of each sector from region $n$

10.1029/2021EF002132

to region $m$; $Z_{ij}^{nm}$ is the intermediate demand from sector in region $n$ to sector $j$ in region $m$; $x_j^m$ is the output of sector $j$ in region $m$; $\mathrm{F}^{\mathbf{nm}} = [F_i^{nm}]$ refers to sector $i$ is produced in region $n$ and finally consumed in region $m$.

To account for the environmental impact, we introduced emission intensity. Emission intensity **E** is defined as per unit output producing $CO_2$ emissions. Then, the consumption-based $CO_2$ emissions can be calculated as follows:

$$\mathbf{C} = \mathbf{E}\left(\mathbf{I} - \mathbf{A}\right)^{-1}\mathbf{F} \tag{2}$$

where **C** is a vector of total $CO_2$ emissions in goods and services used for final demand; $\mathbf{E} = \left[e_i^n\right]$ is the matrix of emission intensity; $e_i^n = \frac{CE_i^n}{X_i^n}$ represents emission intensity of sector $i$ in region $n$; $CE_i^n$ is $CO_2$ emission inventory for sector in region $n$; $\left(\mathbf{I} - \mathbf{A}\right)^{-1}$ and **F** are the same as mentioned above, which represent the Leontief inverse matrix and final demand, respectively. Notably, carbon emissions embodied in the imports are not included in the study due to the high uncertainty of nesting the city-level MRIO model into the global MRIO model.

### 3.2. Structural Decomposition Analysis

Structural decomposition analysis (SDA) is usually used to identify the drivers of $CO_2$ emissions changes (Casler & Rose, 1998; Xu & Dietzenbacher, 2014). Here, we decomposed the final demand **F** into consumption structure ($\mathbf{Y_s}$), consumption per capita ($\mathbf{Y_c}$) and population ($P$). The SDA equation with five driving factors can be expressed as:

$$\Delta\mathbf{C} = \mathbf{C}_1 - \mathbf{C_o} = \left(\Delta\mathbf{E}\right)\mathbf{L}\mathbf{Y_s}\mathbf{Y_c}P + \mathbf{E}\left(\Delta\mathbf{L}\right)\mathbf{Y_s}\mathbf{Y_c}P + \mathbf{E}\mathbf{L}\left(\Delta\mathbf{Y_s}\right)\mathbf{Y_c}P + \mathbf{E}\mathbf{L}\mathbf{Y_s}(\Delta\mathbf{Y_c})P + \mathbf{E}\mathbf{L}\mathbf{Y_s}\mathbf{Y_c}\left(\Delta P\right) \tag{3}$$

where 1 and 0 represent the calculation period. In our study, 0 refers to the year 2012, and 1 refers to the year 2015. Δ denotes the change of the factor during the period. Usually, five factors have 5! = 120 decomposition forms. Here, we address this issue based on the average of two polar decompositions (Dietzenbacher & Los, 1998). The influence of each factor can be respectively illustrated as:

$$\Delta\mathbf{C_E} = \frac{1}{2}\left(\Delta\mathbf{E}\mathbf{L}_1\mathbf{Y}_{\mathbf{s}1}\mathbf{Y}_{\mathbf{c}1}P_1 + \Delta\mathbf{E}_0\mathbf{L}_0\mathbf{Y}_{\mathbf{s}0}\mathbf{Y}_{\mathbf{c}0}P_0\right)$$

$$\Delta\mathbf{C_L} = \frac{1}{2}\left(\mathbf{E}\Delta\mathbf{L}_1\mathbf{Y}_{\mathbf{s}1}\mathbf{Y}_{\mathbf{c}1}P_1 + \mathbf{E}_0\Delta\mathbf{L}_0\mathbf{Y}_{\mathbf{s}0}\mathbf{Y}_{\mathbf{c}0}P_0\right)$$

$$\Delta\mathbf{C}_{\mathbf{Y_s}} = \frac{1}{2}\left(\mathbf{E}\mathbf{L}_1\Delta\mathbf{Y}_{\mathbf{s}1}\mathbf{Y}_{\mathbf{c}1}P_1 + \Delta\mathbf{E}_0\mathbf{L}_0\Delta\mathbf{Y}_{\mathbf{s}0}\mathbf{Y}_{\mathbf{c}0}P_0\right)$$

$$\Delta\mathbf{C}_{\mathbf{Y_C}} = \frac{1}{2}\left(\mathbf{E}\mathbf{L}_1\mathbf{Y}_{\mathbf{s}1}\Delta\mathbf{Y}_{\mathbf{c}1}P_1 + \mathbf{E}_0\mathbf{L}_0\mathbf{Y}_{\mathbf{s}0}\Delta\mathbf{Y}_{\mathbf{c}0}P_0\right)$$

$$\Delta\mathbf{C_P} = \frac{1}{2}\left(\mathbf{E}\mathbf{L}_1\mathbf{Y}_{\mathbf{s}1}\mathbf{Y}_{\mathbf{c}1}\Delta P_1 + \mathbf{E}_0\mathbf{L}_0\mathbf{Y}_{\mathbf{s}0}\mathbf{Y}_{\mathbf{c}0}\Delta P_0\right)$$

where $\Delta\mathbf{C_E}$ indicates the impact from emission intensity changes; $\Delta\mathbf{C_L}$ represents the impact of changes in production structure; $\Delta\mathbf{C}_{\mathbf{Y_s}}$ refers to the impact due to consumption structure changes; $\Delta\mathbf{C}_{\mathbf{Y_C}}$ and $\Delta\mathbf{C_P}$ represents the impact of changes in per capita consumption and population, respectively. The sum of the changes of $CO_2$ emissions in five factors is equal to $\Delta\mathbf{C}$.

10.1029/2021EF002132

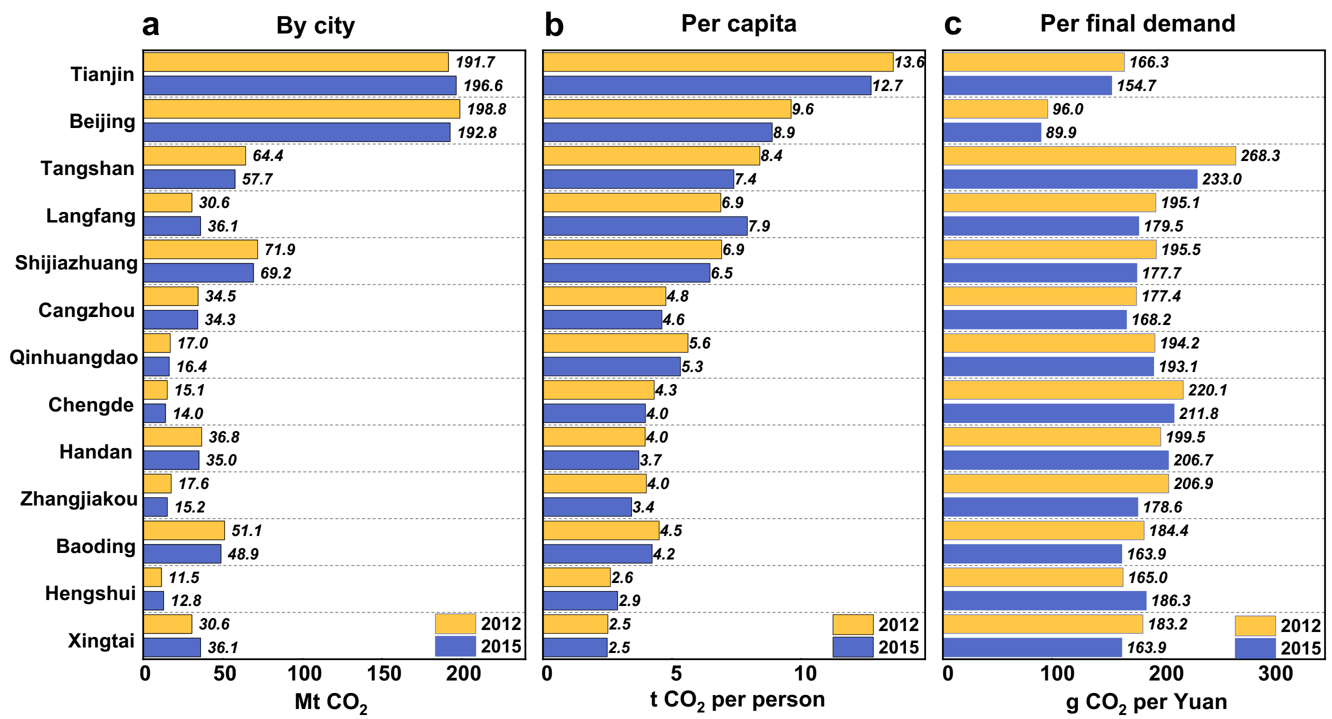


**Figure 1.** The consumption-based carbon emissions of 13 cities in 2012 and 2015. The figure shows the total of each city's consumption-based carbon emissions (a), per capita consumption-based carbon emissions (b), consumption-based carbon emissions of per unit final demand(c). The city ranking is in descending order of gross domestic product (GDP) per capita in 2015. Mt means million tonnes, t means tonne, and g means gram.

### 3.3. Data Source and Process

The city-level multiregional input-output tables wereconstructed adopting the maximum-entropy approach to build. The construction method can be found in reference (Zheng et al., 2021). The statistical data such as exports and imports and transport data are from China's customs data and national railway statistical data. The constructed Jing-Jin-Ji city-level MRIO table includes 41 areas: 11 cities in Hebei province and 30 provinces and municipalities in China. Each area contains 42 economic sectors, which is the same as the provincial IO table in China. We combined 42 sectors into 6 sectors. The aggregated sectors are shown in Table S1.

Both the city-level MRIO tables of 2012 and 2015 were compiled using current year prices. Therefore, to eliminate the influence of price, we chose 2012 as the price benchmark year and converted the prices of 2015 MRIO table into 2012 prices. Here, we used different sector price indexes in each area, including the agriculture producer price index, the industry producer price index, the fixed asset investment price index and the consumer price index. For 11 cities in Hebei province, the province's price indexes were unified used. The mentioned data are all from the statistic yearbooks of provinces and cities. The official data of population and regional GDP are all from China's statistic yearbook.

## 4. Results

### 4.1. Consumption-Based $CO_2$ Emissions in 13 Cities

The total consumption-based emissions of Jing-Jin-Ji urban agglomeration slightly decreased, from 758.9 Mt in 2012 to 747.2 Mt in 2015. Beijing and Tianjin were the two largest contributors of total consumption-based emissions in Jing-Jin-Ji, contributing to 51.4% in 2012, and slightly more, 52.1% in 2015 (Figure 1a). But in 2012, the consumption-based emissions of Beijing shrunk slightly by 3.0%, and Tianjin overtook Beijing as the largest contributor (196.6 Mt $CO_2$). Compared with Beijing and Tianjin, the consumption-based emissions of cities in Hebei province were significantly lower. Shijiazhuang was the largest contributor to consumption-based emissions in Hebei province, while Hengshui was the smallest. The consumption-based emissions in Beijing (198.8 Mt $CO_2$) were more than 17 times those of Hengshui (11.5 Mt $CO_2$) in 2012, and this gap shrunk to 15 times in 2015. Although Beijing and Tianjin's total consumption-based emissions were similar, their annual per capita consumption-based emissions varied widely (Figure 1b). The per capita consumption-based carbon emissions in Beijing (9.6 t $CO_2$ per person) were only equal to three-quarters of Tianjin (13.6 t $CO_2$ per person) in 2012, and both of them saw a decrease of 7.6% and 6.3%, respectively in 2015. This may be due to Tianjin having poor public transport and infrastructure compared with Beijing, and per capita carbon emissions were higher. With the construction of low-carbon cities, per capita carbon emissions should gradually decline (Bhoyar et al., 2014).

In addition, all of the cities per final demand of consumption-based carbon emissions in Hebei province were higher than Beijing and Tianjin in 2012 and 2015 (Figure 1c). Per final demand of consumption-based emissions, also named multiplier, is calculated from consumption-based emissions divided by final demand. Not the same as emission intensity, which only reflects direct production-based emissions efficiency, the multiplier indicates the total embodied emissions of each Yuan expenditure (Wood & Dey, 2009). As we can see, the per final demand of consumption-based emissions in Tangshan (268.3 g $CO_2$ per Yuan) was up to 2.8 times that of Beijing (96.0 g $CO_2$ per Yuan), while their per capita emissions were similar. It reveals that the industry aggregation in Beijing and Tianjin has more significant economies of scale, which boosts productivity growth and reduces emissions per Yuan of consumption. Compared to 2012, most cities' consumption-based emissions per final demand declined significantly. Tangshan, Shijiazhuang, and Baoding decreased by 13.1%, 9.1%, and 11.1%, respectively in 2015. It can be seen that people's consumption structure has changed to be cleaner. In general, people living in megacities have more opportunities to access and prefer low-carbon lifestyles, such as the demand for the service industry. Less developed regions are more dependent on high carbon emissions products like agricultural and energy consumption. Along with economic development, the rapid growth of per final demand consumption-based emissions in Jing-Jin-Ji will decrease continually.

From the perspective of sector characteristics (Figure 2a), there is not so much difference in key sectors of consumption-based carbon emissions in various cities, which concentrated on the construction sectors. The construction sector was the largest contributor to Tianjin's consumption-based carbon emissions during 2012 and 2015, accounting for 52.0% of the total emissions in 2012, increasing to 68.6% in 2015. With the rapid increase in urban construction under the new normal era, the increase of construction-related emissions offset the heavy industry and agriculture mitigation and led to Tianjin having higher consumption-based emissions in 2015. As for Beijing, both the services and construction sectors shaped the consumption-based carbon emissions, accounting for 38.6% and 28.5% in 2012, respectively, and construction-related carbon emissions grew consistently, reaching 37.3% in 2015 due to public infrastructure construction. The proportion in consumption-based emissions induced by services was more than twice that of Tianjin and seven times that of Tangshan, reflecting more demand for the service sector in Beijing than in other cities.

Figure 2b highlights the distinct role and change trends in consumption-based emissions and production-based emissions from 2012 to 2015 in each city. The proportion indicates each cities carbon emissions accounted for how much (percent) in Jin-Jin-Ji total consumption-based and production-based emissions. It was calculated by each cities consumption-based or production-based carbon emissions divided by total emissions, respectively. The cities beyond the dotted line show that their proportion of production-based emissions is higher than it in consumption-based emissions, while the cities below the dotted line refer to lower production-based emissions rates than the consumption-based ones. It can be clearly seen that Tangshan, Shijiazhuang, Handan were typical suppliers in the Jing-Jin-Ji urban agglomeration, due to its heavy manufactory structure. Tangshan was responsible for a quarter of Jing-Jin-Ji's total production-based carbon emissions in 2012, decreasing to 21.4% in 2015. It is followed by Shijiazhuang and Handan, whose emissions accounted for 12.1%and 11.1% of total consumption-based emissions, respectively. In our study period, there was a weakening trend in Tangshan as a carbon supplier. At the same time, Handan's and Shijiazhuang's production-based emissions rose consistently, and Handan overtook Shijiazhuang becoming the second-largest production-based contributor in the Jing-Jin-Ji urban agglomeration. By contrast, Beijing and Tianjin were the two biggest consumers over the 3 years. Beijing contributed over 26.2% of total consumption-based emissions in 2012, but less than 10% of total production-based emissions. Compared with Beijing, Tianjin was not only a consumer but also a supplier. It was responsible for 15% of production-based

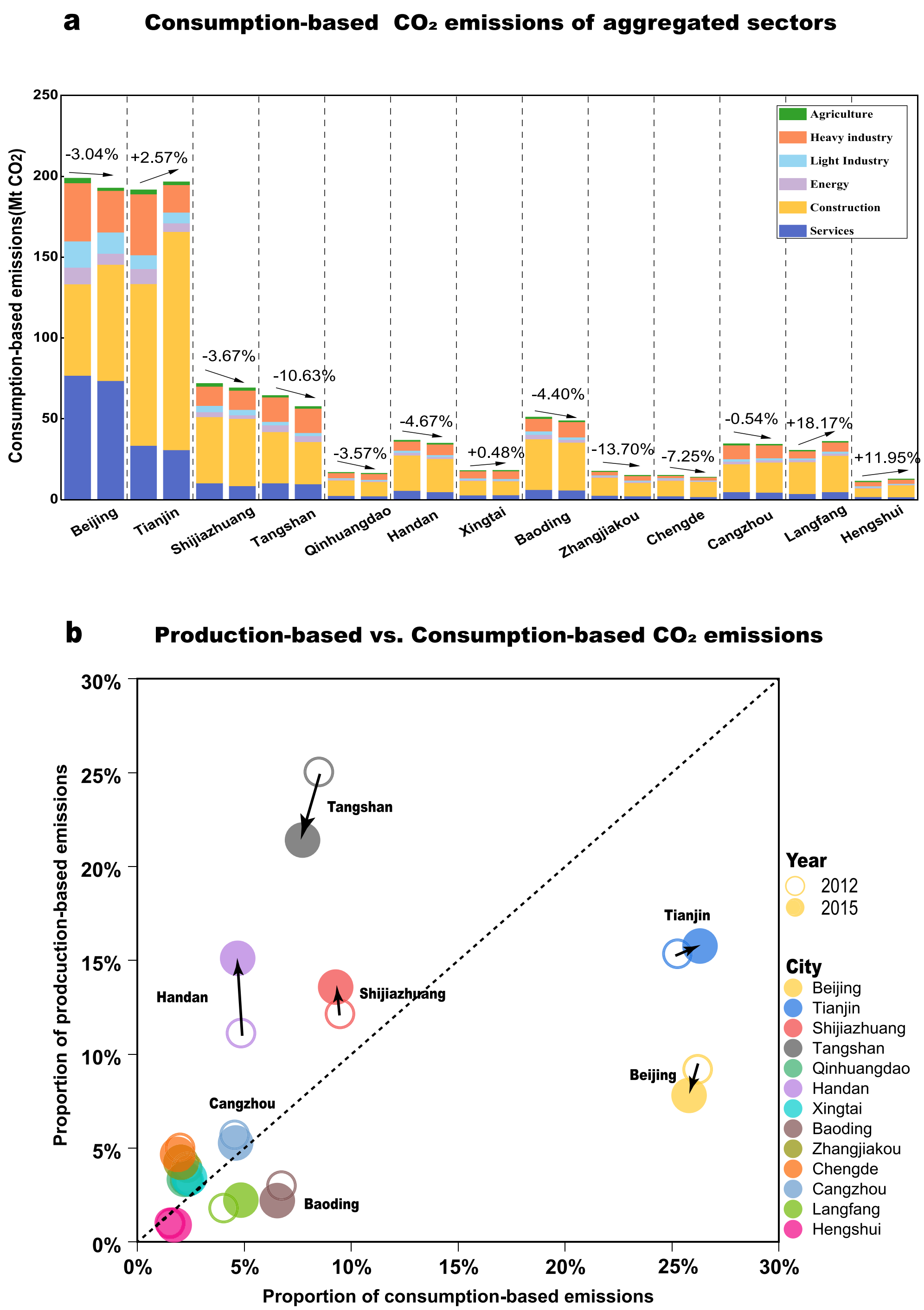


**Figure 2.** Consumption-based $CO_2$ emissions of aggregated sectors in 13 cities in 2012 and 2015 (a), and the proportion of consumption-based emissions and production-based emissions (b). Mt means million tonnes.

emissions and both production-based and consumption-based emissions increased slightly from 2012 to 2015.

### 4.2. Emissions Embodied in Trade

Trade-related carbon emissions in Jing-Jin-Ji were 362.2 Mt in 2012, decreasing to 341.2 Mt in 2015, of which 64.5% emissions were from Tangshan, Tianjin, Shijiazhuang, and Handan in 2012, and the propor-

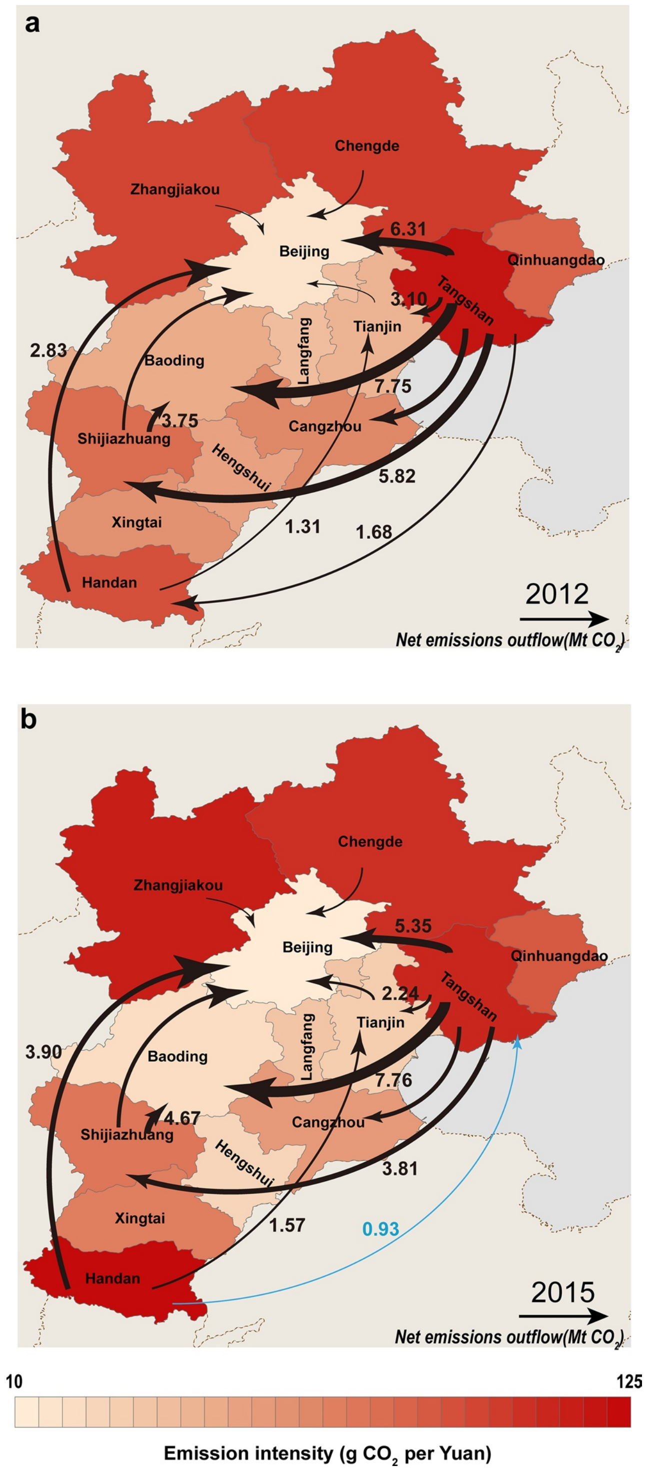


**Figure 3.** Changes in emissions flow in the Jing-Jin-Ji urban agglomeration from 2012 to 2015. The color represents emission intensity in 13 cities. The size of arrows indicates the number of net flows between cities. Mt means million tonnes.

tion increased to 66.7% in 2015. Among them, Tangshan was the largest contributor: trade-related emissions to Jing-Jin-Ji were 80.5 Mt $CO_2$ in 2012, only 20.9% of which used to meet its own demands. Although the trade-related emissions had decreased, 20.1% of carbon emissions in Tangshan were still used to supply other cities in 2015. By contrast, Tianjin was the second-largest supplier, but with more than 90% of its embodied carbon emissions used for local production in 2012.

In terms of net carbon emissions (Figure 3), from 2012 to 2015, the net carbon flow of the Jing-Jin-Ji urban agglomeration remained largely unchanged, except for the reflux between Tangshan and Handan. In the economic transition, manufactory-based cities such as Tangshan, Shijiazhuang, and Handan were still located upstream of the supply chain, providing high emission intensity raw materials for cities in the Jin-Jin-Ji urban agglomeration. Tangshan, Handan, and Shijiazhuang generated 53.7 Mt net carbon emissions in 2012, and this figure increased to 58.8 Mt in 2015. Tangshan's net export carbon emission was 38.8 Mt, dropping by 23.8% in 2015. More than half of these net emissions flowed in Baoding, Beijing, and Shijiazhuang. Handan was the second-largest net outflow supplier, supplying 11 cities with about 10.9 Mt in 2012, and increasing sharply to supplying 12 cities totaling 22.8 Mt in 2015. This is because of the sharp increase in Handan's emission intensity due to undertook the high carbon-intensive factories from Beijing, causing carbon transfer reflux from inflowing 1.7 Mt in 2012 to outflowing 0.9 Mt in 2015. In addition, Beijing and Tianjin were at the end of the supply chain, inflowing 17.1 Mt and 7.9 Mt net trade-related carbon emissions from upstream cities like Tangshan and Handan in 2012. It reveals that Beijing and Tianjin exported low-carbon products while importing high-carbon products through inter-city trade. The advantages and disadvantages of city carbon mitigation did not change substantially in the economic transition era. The largely hidden emissions were still from high emission intensity cities to low emission intensity cities. Low carbon-intensive cities like Beijing and Tianjin reduced their mitigation pressures through interregional trade, while high carbon-intensive cities in Hebei province undertook more mitigation stress.

The heavy industrial sector and energy sectors were the primary source of trade-related carbon emissions in Jing-Jin-Ji, driven by the demand from Tianjin and Shijiazhuang through the supply chain. Heavy industry and energy emissions (Figures 4a and 4c) accounted for 84.7% of the total trade-related carbon emissions in 2012 and 84.3% in 2015. For heavy industry, 72.2% of carbon emissions were from Tangshan, Shijiazhuang, Tianjin and Handan in 2012, and saw minimal change by 2015 at 72.5%. Tangshan was the largest heavy industry-related carbon supplier, accounting for 27.9% in 2012 and 23.1% in 2015 of trade-related heavy industry emissions. Handan over took Shijiazhuang and Tianjin, supplying about 19.9% of heavy industry emissions in 2015. The construction sector was responsible for 63.9% and 63.2% of trade-related carbon emissions from heavy industry in 2012 and 2015, respectively. This is because construction activity requires a lot of energy-intensive intermediate products, like iron, etc. In addition, Tianjin and Shijiazhuang were the pri-

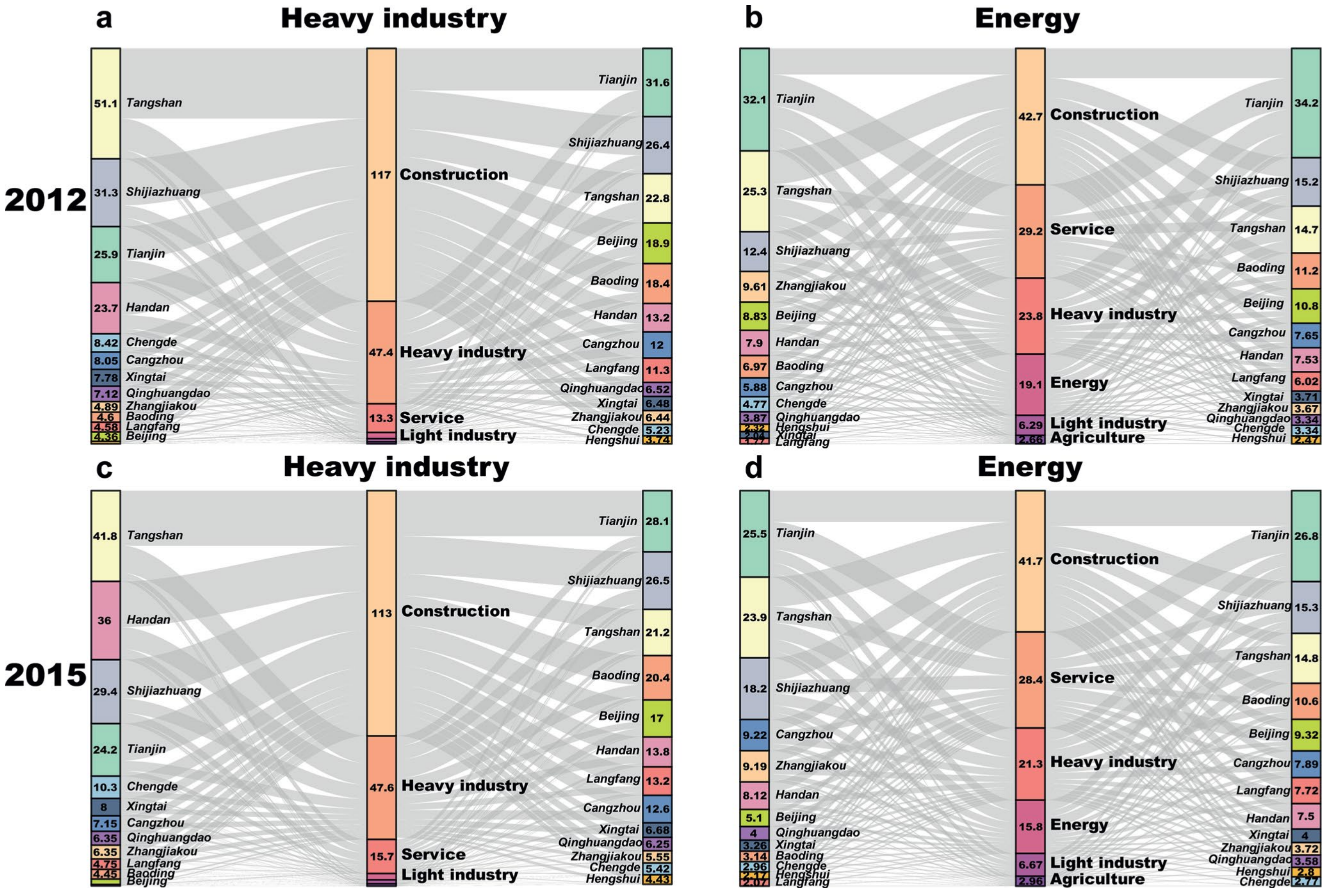


**Figure 4.** Carbon flows for heavy industry and energy sector in the Jing-Jin-Ji urban agglomeration. The 2012 carbon flows for heavy industry (a) and carbon flow for the energy industry (b). The 2015 carbon flows for heavy industry (c), and energy industry (d).

mary consumers in the heavy industry supply chain. But, heavy industry emissions driven by Tianjin and Shijiazhuang decreased by 27.3% in 2015. It can be seen that heavy-industrial cities like Tangshan and Handan, provided high carbon-intensive raw materials to meet demand in Tianjin and Shijiazhuang for construction and heavy industrial activities.

A further look at the energy-related embodied carbon emissions (Figures 4b and 4d) shows that almost 123.8 Mt and 116.8 Mt were emitted in the energy sector in 2012 and 2015, respectively. Similarly, in 2012, construction-induced emissions accounted for 34.5% of total energy-related emissions, and service-induced emissions accounted for 23.6%. Tianjin, Tangshan, and Shijiazhuang were both on the supply and demand sides of the energy supply chain, accounting for 56.4% of energy trade-related emissions in 2012 and increasing to 57.9% in 2015. However, 51.8% and 48.7% of energy-related emissions were released for their own construction and service sector demands in 2012 and 2015, respectively. Unlike heavy industry, Tianjin was the largest producer and consumer in energy-related carbon emissions, indicating that Tianjin's power supply mainly went to meet its local demand. In sum, Tangshan, Shijiazhuang, and Tianjin shaped Jing-Jin-Ji's main carbon supply chain both from the production and consumption sides. Therefore, more attention needs to be paid to these cities and high-carbon sectors, if the mitigation targets of Jing-Jin-Ji are to be met.

### 4.3. The Driving Force in Consumption-Based Carbon Emissions Changes

In China's economic transition, emission intensity is the most important factor to restrain the growth of total carbon emission in the Jing-Jin-Ji, which reduced consumption-based emissions by 13.5% of emissions from 2012 to 2015 (Figure 5). The decline of emission intensity offset the increase in carbon emissions caused by consumption structure (+10.8 Mt), per capita consumption (+64.6 Mt), and population


**Figure 5.** Drivers of changes in consumption-based emissions in 13 cities from 2012 to 2015. The color represents different driving forces. The width of the column corresponds to the number of carbon emissions. Mt means million tonnes.

(+34.4 Mt). From the city perspective, the decline in consumption-based emissions was mainly driven by Beijing and Tianjin with a contribution rate of 27.9% and 25.7% of total emissions, respectively. This can be mainly attributed to the strict policy and administrative capacity in the economic transition era. During the 12th 5-year plan (2010–2015), Tianjin shut down small thermal power plants and was strenuous in its efforts to develop new energy and new materials, including green batteries, wind power (Tianjin Development and Reform Commission, 2012a, 2012b). Beijing also put more emphasis on the low-carbon transition in energy structure. But, the rapid decline in Beijing's emission intensity was largely dependent on the relocation of heavy industry factories to Hebei and Tianjin as well (Beijing Municipal Ecology and Environment Bureau, 2014). For instance, the Capital Iron and Steel Company and Beijing Lingyun Chemical Plant, both resource-intensive industries with high energy consumption, have been relocated to Hebei province. The relocation of these industries hinders emission intensity from declining in cities of Hebei province. It can be seen in Figure 5 that Tangshan, Shijiazhuang, and Baoding only reduced their carbon emissions by 8.6 Mt, 9.4 Mt, 8.4 Mt due to changes in emission intensity.

Moreover, under the economic transition, the change in production structure was another driver of consumption-based emissions reduction, cutting about 18.9 Mt $CO_2$ in total. The inhibiting effect of changes in production structure indicates that Jing-Jin-Ji urban agglomeration was more to optimize of production structure. The change in Tianjin's production structure had the largest contributions to emissions mitigation in the Jing-Jin-Ji urban agglomeration, with a decrease of 8.9 Mt $CO_2$. In the economic transition, Tianjin used its obvious advantages by developing an export-oriented economy and focused on the development of its tertiary industry. In 2015, the tertiary industry of Tianjin first overtook the secondary sector and became the leading industry.

The optimization of the production structure led to massive carbon emissions reduction in Tianjin. However, changes in production structure in Tangshan and Handan had very little effect, reducing emissions by 1.6 Mt $CO_2$ respectively, and production structure changes in Shijiazhuang reduced only 1.1 Mt $CO_2$ as well. There is a great potential for cities in Hebei province to reduce emissions through upgrading production structure.

Conversely, changes in per capita consumption and population growth were the primary forces to increase consumption-based emissions of 64.6 Mt $CO_2$ and 34.4 Mt $CO_2$, respectively. Compared with cities in Hebei province, the growth of population had the largest effect on increasing Beijing and Tianjin carbon emissions, especially Tianjin leading with 17.6 Mt. This is mainly due to the population growth rate of Tianjin reached up 9.5%, nearly double that of Beijing from 2012 to 2015. It should be notice that although population growth had little effect on cities in Hebei province, the population aggregation in Beijing and Tianjin also led to carbon emissions increasing to undeveloped cities. The higher carbon demand led by Beijing and Tianjin would transfer to cities in Hebei province through supply chain. Thus, Beijing and Tianjin should assume more responsibility for regional emissions mitigation. In addition, the extreme imbalance between the megacities and undeveloped cities in terms of professional expertize also further limits the effectiveness of mitigation. Professional and technical skills are far too concentrated in Beijing and Tianjin. Due to the lack of expertize in new technology, industry development in Hebei province is restricted to low technology and high carbon-intensive industries. In order to deal with this imbalance, policies are needed in Hebei that will attract the right kind of expertize as well as promote skilled labor mobility across the Jing-Jin-Ji urban agglomeration. The infrastructure and public service facilities in Hebei province need to be strengthened as well, so as to retain its skilled workforce to develop its high-tech industry.

## 5. Conclusions

Our results show that the total consumption-based carbon emissions of Jing-Jin-Ji have decreased during 2012–2015. A further look at cities, there is a declining trend in most cities, such as Beijing, Shijiazhuang, and Tangshan (Figure 1). Although decreasing trends are the theme, emissions in Tianjin and partially undeveloped cities of Hebei province have increased slightly. The results show similarities with previous studies. For instance, Fan et al., (2019) revealed the consumption-based emissions fluctuation in Beijing from 1997-2012, which increased first and then decreased, and the $CO_2$ emissions of both Tianjin and Hebei have been shown continued growth in their study period. In our study, we extended the time period to 2015 and found the general decreasing trend is continuing. Only some undeveloped cities of Hebei showed the opposite situation. We also find that substantial carbon leakage has been transferred to cities in Hebei province for mega cities such as Beijing and Tianjin. Particularly in Tangshan of Hebei province, the largest supplier in selected city agglomeration, more than one-fifth of net carbon flowed to Beijing and Tianjin in 2012 and 2015 (Figures 2 and 3). The same phenomenon can be also seen in Zheng, Zhang, et al., 2019 results: Beijing and Tianjin led by consumption-based carbon emissions, while cities in Hebei province acted as suppliers. In the economic transition, although the consumption-based $CO_2$ emissions decreased, the carbon flow direction didn't change, which points to cities in Hebei province were facing increasing challenges in future mitigation measurements, if there demand from consumption side was not changed.

When looking into driving forces that affected consumption-based carbon emissions, five driving factors impact on 13 cities differently (Figure 5). First, emission intensity is found as the largest trigger of Jing-Jin-Ji carbon emissions deceleration as a whole. Until now, effort made in energy mix has already benefited Jing-Jin-Ji to a large extent. For example, due to improving the use of secondary energy sources, such as coke, gasoline, diesel, Beijing, and Tianjin reduced large $CO_2$ emissions (Yu et al., 2021). But, although emissions intensity of both Beijing and Tianjin have declined obviously, cities in Hebei province still have room for that. Not just the emission intensity, we also find despite the energy consumption per GDP (energy consumption intensity) has decreased, but it still stayed at a high level (Jia, 2017). Compared with megacities such as Beijing and Tianjin, cities of Hebei are found at a lower speed in emission mitigation actions. This is partially caused by historical economic development such as heavy industry is one of the pillar industries of those areas. The movement toward industrial optimization and further emission reduction demand more restrictive and powerful measurements from top-down, otherwise those mitigations target in undeveloped cities are hardly achieved in the short term. Third, we still need to note that population growth is another potential factor that upgrading emission, especially for the booming population of megacities that may further transfer their additive carbon emission to undeveloped cities. Therefore, the unbalanced development of city agglomeration is also an unavoidable issue to be addressed in the future.

In general, although the results are not representative of all the cities in China, the information provided is of great importance to show the problem as well as opportunities for the carbon-intensive areas (especially with unequal development). One of the policy implications is that we highlight the importance of developing subregional study in China, which is already pointed out in many previous studies but still demand further information in city level. With series of national emission reduction targets proposed, how to fairly and reasonably allocate emission mitigation goals to sub-national regions has become an issue (Long et al., 2021). In our study, we focused on city-level carbon emissions patterns from a consumption-based perspective, which can fairly reveal each city's responsibility for emissions. Here, we suggest Beijing and Tianjin need to undertake more responsibilities, and policymakers should attach importance to undeveloped cities in Hebei province when setting emissions reduction goals. Due to carbon leakage having an impact on the neighboring cities, this study reminds that: when a city makes its plan to reduce carbon emissions, particularly inside the urban agglomeration, should also consider the neighboring cities as well (Yu et al., 2020). Another policy implication is that we revealed the temporal heterogeneity of emission patterns and their driving factors. 2012–2015 is during the twelfth 5-year plan period, which is a stage to transform the economic growth pattern. Knowing emissions patterns in this stage can help better understand the 13th 5-Year Plan (2016–2020) emissions mitigation achievements and instruct 14th (2021–2025) plan. Our results show Jing-Jin-Ji's total consumption-based carbon emissions decreased in the economic transition. Declined emission intensity is the biggest cause of emissions deceleration. It implies the importance of improving energy efficiency and updating the energy mix, such as replacing coal with natural gas and vigorously developing renewable energy. Finally, rapid urbanization promotes industrial growth, as well as exerts great pressure on urban environment we are living in (P. P. Wang et al., 2021). By 2030, nearly 710 million residents will live in the urban agglomeration globally (United Nations, 2016), which implies that reducing $CO_2$ emissions will become a top priority in urban agglomerations in the future. In this sense, understanding urban emission patterns from sub-regional will also be a research hotspot. We expect future studies can show how to achieve subnational urban development planning with low carbon emission under special economic development stages, which is also in line with the national carbon emission target.

## Data Availability Statement

All datasets are available online (https://doi.org/10.5281/zenodo.4679349), including: (a) 2012 and 2015 Jing-Jin-Ji city-level MRIO_Table (41 Regions* 42 Sectors); (b) 2012 and 2015 Carbon inventory (41 Regions* 42 Sectors); (c) Price_Index (2012/2015). The updated MRIO table and $CO_2$ inventory can be found in China Emission Accounts and Datasets (https://www.ceads.net/) for free download. The Statistical Yearbooks Database is publicly available and can be downloaded in the (http://tongji.oversea.cnki.net/oversea/engnavi/navidefault.aspx).

**Acknowledgments**
This work was supported by the National Natural Science Foundation of China (41921005), the UK Natural Environment Research Council (NE/P019900/1 and NE/V002414/1), and the Norwegian Research Council (287690/F20).

## References

Barrett, J., Peters, G., Wiedmann, T., Scott, K., Lenzen, M., Roelich, K., & Quéré, C. L. (2013). Consumption-based GHG emission accounting: A UK case study. *Climate Policy*, *13*(4), 451–470. https://doi.org/10.1080/14693062.2013.788858

Beijing Municipal Ecology and Environment Bureau. (2014). *Catalogue of Beijing's industrial polluting industries, production process adjustment and equipment elimination*.

Bhoyar, S. P., Dusad, S., Shrivastava, R., Mishra, S., Gupta, N., & Rao, A. B. (2014). Understanding the impact of lifestyle on individual carbon-footprint. *Procedia-Social and Behavioral Sciences*, *133*, 47–60. https://doi.org/10.1016/j.sbspro.2014.04.168

Bin, S., & Dowlatabadi, H. (2005). Consumer lifestyle approach to US energy use and the related $CO_2$ emissions. *Energy Policy*, *33*(2), 197–208. https://doi.org/10.1016/S0301-4215(03)00210-6

Casler, S. D., & Rose, A. (1998). Carbon dioxide emissions in the U.S. economy: A structural decomposition analysis. *Environmental and Resource Economics*, *11*(3), 349–363. https://doi.org/10.1023/A:1008224101980

Chen, H., & Chen, W. (2019). Carbon mitigation of China's building sector on city-level: Pathway and policy implications by a low-carbon province case study. *Journal of Cleaner Production*, *224*, 207–217. https://doi.org/10.1016/j.jclepro.2018.12.022

Chen, J., Yuan, H., Tian, X., Zhang, Y., & Shi, F. (2019). What determines the diversity of $CO_2$ emission patterns in the Beijing-Tianjin-Hebei region of China? An analysis focusing on industrial structure change. *Journal of Cleaner Production*, *228*, 1088–1098. https://doi.org/10.1016/j.jclepro.2019.04.267

Chen, W., Wu, S., Lei, Y., & Li, S. (2017). Interprovincial transfer of embodied energy between the Jing-Jin-Ji area and other provinces in China: A quantification using interprovincial input-output model. *The Science of the Total Environment*, *584*(585), 990–1003. https://doi.org/10.1016/j.scitotenv.2017.01.152

Chen, Z.-M., Ohshita, S., Lenzen, M., Wiedmann, T., Jiborn, M., Chen, B., et al. (2018). Consumption-based greenhouse gas emissions accounting with capital stock change highlights dynamics of fast-developing countries. *Nature Communications*, *9*(1), 3581. https://doi.org/10.1038/s41467-018-05905-y

Davis, S. J., & Caldeira, K. (2010). Consumption-based accounting of $CO_2$ emissions. *Proceedings of the National Academy of Sciences*, *107*(12), 5687–5692. https://doi.org/10.1073/pnas.0906974107

Dietzenbacher, E., & Los, B. (1998). Structural decomposition techniques: sense and sensitivity. *Economic Systems Research*, *10*(4), 307–324. https://doi.org/10.1080/09535319800000023

Druckman, A., & Jackson, T. (2009). The carbon footprint of UK households 1990–2004: A socio-economically disaggregated, quasi-multi-regional input-output model. *Ecological Economics*, *68*(7), 2066–2077. https://doi.org/10.1016/j.ecolecon.2009.01.013

Fan, J.-L., Cao, Z., Zhang, X., Wang, J.-D., & Zhang, M. (2019). Comparative study on the influence of final use structure on carbon emissions in the Beijing-Tianjin-Hebei region. *The Science of the Total Environment*, *668*, 271–282. https://doi.org/10.1016/j.scitotenv.2019.02.363

Feng, K., Davis, S. J., Sun, L., Li, X., Guan, D., Liu, W., et al. (2013). Outsourcing $CO_2$ within China. *Proceedings of the National Academy of Sciences*, *110*(28), 11654–11659. https://doi.org/10.1073/pnas.1219918110

Feng, K., Hubacek, K., Sun, L., & Liu, Z. (2014). Consumption-based $CO_2$ accounting of China's megacities: The case of Beijing, Tianjin, Shanghai and Chongqing. *Ecological Indicators*, *47*, 26–31. https://doi.org/10.1016/j.ecolind.2014.04.045

Green, F., & Stern, N. (2015). *China's "new normal": structural change, better growth, and peak emissions* (p. 64).

Grubb, M., Sha, F., Spencer, T., Hughes, N., Zhang, Z., & Agnolucci, P. (2015). A review of Chinese $CO_2$ emission projections to 2030: The role of economic structure and policy. *Climate Policy*, *15*, S7–S39. https://doi.org/10.1080/14693062.2015.1101307

Guan, D., Hubacek, K., Weber, C. L., Peters, G. P., & Reiner, D. M. (2008). The drivers of Chinese $CO_2$ emissions from 1980 to 2030. *Global Environmental Change*, *18*(4), 626–634. https://doi.org/10.1016/j.gloenvcha.2008.08.001

Guan, D., Meng, J., Reiner, D. M., Zhang, N., Shan, Y., Mi, Z., et al. (2018). Structural decline in China's $CO_2$ emissions through transitions in industry and energy systems. *Nature Geoscience*, *11*(8), 551–555. https://doi.org/10.1038/s41561-018-0161-1

Hasegawa, R., Kagawa, S., & Tsukui, M. (2015). Carbon footprint analysis through constructing a multi-region input-output table: A case study of Japan. *Journal of Economic Structures*, *4*(1). https://doi.org/10.1186/s40008-015-0015-6

Heinonen, J., & Junnila, S. (2011). Implications of urban structure on carbon consumption in metropolitan areas. *Environmental Research Letters*, *6*(1), 014018. https://doi.org/10.1088/1748-9326/6/1/014018

Heinonen, J., Ottelin, J., Ala-Mantila, S., Wiedmann, T., Clarke, J., & Junnila, S. (2020). Spatial consumption-based carbon footprint assessments: A review of recent developments in the field. *Journal of Cleaner Production*, *256*, 120335. https://doi.org/10.1016/j.jclepro.2020.120335

Huang, Q., Zheng, H., Li, J., Meng, J., Liu, Y., Wang, Z., et al. (2021). Heterogeneity of consumption-based carbon emissions and driving forces in Indian states. *Advances in Applied Energy*, *100039*. https://doi.org/10.1016/j.adapen.2021.100039

IPCC. (2006). *Guidelines for national greenhouse gas inventories*. Institute for Global Environmental Strategies (IGES).

Jackson, R. B., Canadell, J. G., Le Quéré, C., Andrew, R. M., Korsbakken, J. I., Peters, G. P., & Nakicenovic, N. (2016). Reaching peak emissions. *Nature Climate Change*, *6*(1), 7–10. https://doi.org/10.1038/nclimate2892

Jia, P. (2017). *Beijing, Tianjin and Hebei low-carbon development index research report*. Retrieved from http://tech.sina.com.cn/d/v/2017-09-13/doc-ifykusey9741972.shtml

Knight, K. W., & Schor, J. B. (2014). Economic growth and climate change: A cross-national analysis of territorial and consumption-based carbon emissions in high-income countries. *Sustainability*, *6*(6), 3722–3731. https://doi.org/10.3390/su6063722

Leontief, W. (1986). *Input-output economics*. Oxford University Press.

Li, X., Yang, L., Zheng, H., Shan, Y., Zhang, Z., Song, M., et al. (2019). City-level water-energy nexus in Beijing-Tianjin-Hebei region. *Applied Energy*, *235*, 827–834. https://doi.org/10.1016/j.apenergy.2018.10.097

Long, Y., & Yoshida, Y. (2018). Quantifying city-scale emission responsibility based on input-output analysis: Insight from Tokyo, Japan. *Applied Energy*, *218*, 349–360. https://doi.org/10.1016/j.apenergy.2018.02.167

Long, Y., Yoshida, Y., Liu, Q., Guan, D., Zheng, H., Li, Y., & Gasparatos, A. (2021). Japanese carbon emissions patterns shifted following the 2008 financial crisis and the 2011 Tohoku earthquake. *Communications Earth & Environment*, *2*, (1). https://doi.org/10.1038/s43247-021-00194-8

Meng, J., Mi, Z., Yang, H., Shan, Y., Guan, D., & Liu, J. (2017). The consumption-based black carbon emissions of China's megacities. *Journal of Cleaner Production*, *161*, 1275–1282. https://doi.org/10.1016/j.jclepro.2017.02.185

Mi, Z., Meng, J., Guan, D., Shan, Y., Song, M., Wei, Y.-M., et al. (2017). Chinese $CO_2$ emission flows have reversed since the global financial crisis. *Nature Communications*, *8*(1), 1712. https://doi.org/10.1038/s41467-017-01820-w

Mi, Z., Zhang, Y., Guan, D., Shan, Y., Liu, Z., Cong, R., et al. (2016). Consumption-based emission accounting for Chinese cities. *Applied Energy*, *184*, 1073–1081. https://doi.org/10.1016/j.apenergy.2016.06.094

Mi, Z., Zheng, J., Meng, J., Shan, Y., Zheng, H., Ou, J., et al. (2018). China's energy consumption in the new normal. *Earth's Future*, *6*(7), 1007–1016. https://doi.org/10.1029/2018EF000840

Mi, Z., Zheng, J., Meng, J., Zheng, H., Li, X., Coffman, D., et al. (2019). Carbon emissions of cities from a consumption-based perspective. *Applied Energy*, *235*, 509–518. https://doi.org/10.1016/j.apenergy.2018.10.137

Millward-Hopkins, J., Gouldson, A., Scott, K., Barrett, J., & Sudmant, A. (2017). Uncovering blind spots in urban carbon management: The role of consumption-based carbon accounting in Bristol, UK. *Regional Environmental Change*, *17*(5), 1467–1478. https://doi.org/10.1007/s10113-017-1112-x

National Development and Reform Commission. (2015). *Beijing-Tianjin-Hebei ecological and environmental protection cooperative development plan*.

National Development and Reform Commission. (2016). *The 13th five-year plan*. Retrieved from https://www.ndrc.gov.cn/xxgk/zcfb/ghwb/201603/P020190905497807636210.pdf

National Energy Administration. (2014). *The key to prevent and control coal burning pollution is efficient and clean utilization*. Retrieved from http://www.nea.gov.cn/2014-01/22/c_133064519.htm

Seo, J., Kim, H., & Park, S. (2018). Estimation of $CO_2$ emissions from heavy-duty vehicles in Korea and potential for reduction based on scenario analysis. *The Science of the Total Environment*, *636*, 1192–1201. https://doi.org/10.1016/j.scitotenv.2018.04.269

Shan, Y., Guan, D., Hubacek, K., Zheng, B., Davis, S. J., Jia, L., et al. (2018). City-level climate change mitigation in China. *Science Advances*, *4*(6), eaaq0390. https://doi.org/10.1126/sciadv.aaq0390

Shan, Y., Guan, D., Liu, J., Mi, Z., Liu, Z., Liu, J., et al. (2017). Methodology and applications of city level $CO_2$ emission accounts in China. *Journal of Cleaner Production*, *161*, 1215–1225. https://doi.org/10.1016/j.jclepro.2017.06.075

Shan, Y., Guan, D., Zheng, H., Ou, J., Li, Y., Meng, J., et al. (2018). China $CO_2$ emission accounts 1997–2015. *Scientific Data*, *5*(1), 170201. https://doi.org/10.1038/sdata.2017.201

Shan, Y., Liu, J., Liu, Z., Shao, S., & Guan, D. (2019). An emissions-socioeconomic inventory of Chinese cities. *Scientific Data*, *6*(1). https://doi.org/10.1038/sdata.2019.27

Shao, L., Li, Y., Feng, K., Meng, J., Shan, Y., & Guan, D. (2018). Carbon emission imbalances and the structural paths of Chinese regions. *Applied Energy*, *215*, 396–404. https://doi.org/10.1016/j.apenergy.2018.01.090

Steininger, K. W., Munoz, P., Karstensen, J., Peters, G. P., Strohmaier, R., & Velázquez, E. (2018). Austria's consumption-based greenhouse gas emissions: Identifying sectoral sources and destinations. *Global Environmental Change*, *48*, 226–242. https://doi.org/10.1016/j.gloenvcha.2017.11.011

Su, B., Ang, B. W., & Low, M. (2013). Input-output analysis of $CO_2$ emissions embodied in trade and the driving forces: Processing and normal exports. *Ecological Economics*, *88*, 119–125. https://doi.org/10.1016/j.ecolecon.2013.01.017

Tianjin Development and Reform Commission. (2012a). *Tianjin 12th five-year plan for environmental protection 2012*.

Tianjin Development and Reform Commission. (2012b). *Tianjin's 12th five-year plan for the development of new energy and new materials industry*.

UNDP. (2013). *China national human development report special edition* (p. 348). UNDP.

United Nations. (2016). *The world's cities in 2016*. United Nations. https://doi.org/10.18356/8519891f-en

Wang, C., Zhan, J., Li, Z., Zhang, F., & Zhang, Y. (2019). Structural decomposition analysis of carbon emissions from residential consumption in the Beijing-Tianjin-Hebei region, China. *Journal of Cleaner Production*, *208*, 1357–1364. https://doi.org/10.1016/j.jclepro.2018.09.257

Wang, P. P., Li, Y. P., Huang, G. H., Wang, S. G., Suo, C., & Ma, Y. (2021). A multi-scenario factorial analysis and multi-regional input-output model for analyzing $CO_2$ emission reduction path in Jing-Jin-Ji region. *Journal of Cleaner Production*, *300*, 126782. https://doi.org/10.1016/j.jclepro.2021.126782

Wang, Z., Yang, Y., & Wang, B. (2018). Carbon footprints and embodied $CO_2$ transfers among provinces in China. *Renewable and Sustainable Energy Reviews*, *82*, 1068–1078. https://doi.org/10.1016/j.rser.2017.09.057

Wiedenhofer, D., Guan, D., Liu, Z., Meng, J., Zhang, N., & Wei, Y.-M. (2017). Unequal household carbon footprints in China. *Nature Climate Change*, *7*(1), 75–80. https://doi.org/10.1038/nclimate3165

Wood, R., & Dey, C. J. (2009). Australia's carbon footprint. *Economic Systems Research*, *21*(3), 243–266. https://doi.org/10.1080/09535310903541397

World Steel Association. (2021). *World steel statistics 2021*. Retrieved from https://www.worldsteel.org/zh/dam/jcr:976723ed-74b3-47b4-92f6-81b6a452b86e/WSIF_2021_CN.pdf

Xinhuanet (2020). *We need to focus on carbon neutrality to build beautiful cities*. Retrieved from http://www.xinhuanet.com/energy/2020-11/27/c_1126792175.htm

Xu, Y., & Dietzenbacher, E. (2014). A structural decomposition analysis of the emissions embodied in trade. *Ecological Economics*, *101*, 10–20. https://doi.org/10.1016/j.ecolecon.2014.02.015

Yu, X., Liang, Z., Fan, J., Zhang, J., Luo, Y., & Zhu, X. (2021). Spatial decomposition of city-level $CO_2$ emission changes in Beijing-Tianjin-Hebei. *Journal of Cleaner Production*, *296*, 126613. https://doi.org/10.1016/j.jclepro.2021.126613

Yu, X., Wu, Z., Zheng, H., Li, M., & Tan, T. (2020). How urban agglomeration improve the emission efficiency? A spatial econometric analysis of the Yangtze River Delta urban agglomeration in China. *Journal of Environmental Management*, *260*, 110061. https://doi.org/10.1016/j.jenvman.2019.110061

Zhang, Y., Bai, H., Hou, H., Zhang, Y., Xu, H., Ji, Y., et al. (2021a). Exploring the consumption-based carbon emissions of industrial cities in China: A case study of Tianjin. *Environmental Science and Pollution Research*, *28*(21), 26948–26960. https://doi.org/10.1007/s11356-021-12563-z

Zhang, Y., Wang, H., Liang, S., Xu, M., Liu, W., Li, S., et al. (2014). Temporal and spatial variations in consumption-based carbon dioxide emissions in China. *Renewable and Sustainable Energy Reviews*, *40*, 60–68. https://doi.org/10.1016/j.rser.2014.07.178

Zhang, Y., Wang, Y., & Hou, X. (2019). Carbon mitigation for industrial sectors in the Jing-Jin-Ji urban agglomeration, China. *Sustainability*, *11*(22), 6383. https://doi.org/10.3390/su11226383

Zhang, Z., Meng, J., Zheng, H., Zhu, K., Du, H., & Guan, D. (2020). Production globalization makes China's exports cleaner. *One Earth*, *2*(5), 468–478. https://doi.org/10.1016/j.oneear.2020.04.014

Zhang, Z., Yu, Y., Wang, D., Kharrazi, A., Ren, H., Zhou, W., & Ma, T. (2021b). Socio-economic drivers of rising $CO_2$ emissions at the sectoral and sub-regional levels in the Yangtze River Economic Belt. *Journal of Environmental Management*, *290*, 112617. https://doi.org/10.1016/j.jenvman.2021.112617

Zhao, D., Tang, Y., Liu, J., & Tillotson, M. R. (2017). Water footprint of Jing-Jin-Ji urban agglomeration in China. *Journal of Cleaner Production*, *167*, 919–928. https://doi.org/10.1016/j.jclepro.2017.07.012

Zheng, H., Fath, B. D., & Zhang, Y. (2017). An urban metabolism and carbon footprint analysis of the Jing-Jin-Ji regional agglomeration. *Journal of Industrial Ecology*, *21*(1), 166–179. https://doi.org/10.1111/jiec.12432

Zheng, H., Többen, J., Dietzenbacher, E., Moran, D., Meng, J., Wang, D., & Guan, D. (2021). Entropy-based Chinese city-level MRIO table framework. *Economic Systems Research*. https://doi.org/10.1080/09535314.2021.1932764

Zheng, H., Zhang, Z., Wei, W., Song, M., Dietzenbacher, E., Wang, X., et al. (2020). Regional determinants of China's consumption-based emissions in the economic transition. *Environmental Research Letters*, *15*(7), 074001. https://doi.org/10.1088/1748-9326/ab794f

Zheng, H., Zhang, Z., Zhang, Z., Li, X., Shan, Y., Song, M., et al. (2019a). Mapping carbon and water networks in the North China urban agglomeration. *One Earth*, *1*(1), 126–137. https://doi.org/10.1016/j.oneear.2019.08.015

Zheng, J., Mi, Z., Coffman, D., Shan, Y., Guan, D., & Wang, S. (2019b). The slowdown in China's carbon emissions growth in the new phase of economic development. *One Earth*, *1*(2), 240–253. https://doi.org/10.1016/j.oneear.2019.10.007

Zhu, Q., Peng, X., & Wu, K. (2012). Calculation and decomposition of indirect carbon emissions from residential consumption in China based on the input-output model. *Energy Policy*, *48*, 618–626. https://doi.org/10.1016/j.enpol.2012.05.068