Enlarging Regional Disparities in Energy Intensity within China

Shuai Shao[1,2] , Chang Wang[3] , Yue Guo[4,5] , Lili Yang[6], Shiyi Chen[3], Jinyue Yan[7,8] , Yuli Shan[9] , Zhu Liu[10] , and Dabo Guan[10]

[1]School of Business, East China University of Science and Technology, Shanghai, China, [2]School of Urban and Regional Science, Shanghai University of Finance and Economics, Shanghai, China, [3]School of Economics, Fudan University, Shanghai, China, [4]Key Laboratory of Regional Sustainable Development Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China, [5]College of Resources and Environment, University of Chinese Academy of Sciences, Beijing, China, [6]School of International Economics and Trade, Shanghai Lixin University of Accounting and Finance, Shanghai, China, [7]Department of Chemical Engineering, KTH Royal Institute of Technology, Stockholm, Sweden, [8]School of Business, Society and Energy, Mälardalen University, Västerås, Sweden, [9]Integrated Research on Energy, Environment and Society (IREES), Energy and Sustainability Research Institute Groningen, University of Groningen, Groningen, Netherlands, [10]Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing, China

Abstract As energy saving and emission reduction become a global action, the disparity in energy intensity between different regions is a new rising problem that stems a country's or region's energy-saving potential. Here we collect China's provincial panel data (1995–2017) of primary and final energy consumption to evaluate China's unequal and polarized regional pattern in energy intensity, decompose the inequality index into contributing components, and investigate possible driving factors behind the unequal pattern both regionally and structurally, for the first time. The results show that China's interprovince disparities in energy intensity increase and are exacerbated by the enlarging disparities in energy intensity between the least developed and most developed regions of China. The causes for this phenomenon are as follows: (i) rather loose regulatory measures on mitigating coal consumption; (ii) inferior energy processing technology in areas specializing in energy-intensive industries; (iii) increasing interregional energy fluxes embodied in trade; and (iv) separate jurisdictions at provincial administrative levels. These factors can synthetically result in unintended spillover to areas with inferior green technologies, suggesting an increasingly uneven distribution of energy-intensive and carbon-intensive industries and usage of clean energy. The results reveal the necessities of regional coordination and cooperation to achieve a green economy.

1. Introduction

Although there exist different opinions, energy intensity is one of the basic indicators that are widely used for evaluating the efficiency of comprehensive energy utilization in a country (region) and reflecting the resource and environmental costs of economic development (Bhattacharyya, 2011; Proskuryakova & Kovalev, 2015; Voigt et al., 2014). With the rapid growth of China's energy consumption and greenhouse gas emissions, the contradiction between energy demand and environmental problems has become increasingly prominent, causing problems ranging from ecological system instability and agriculture loss (Kang & Eltahir, 2018; Mi et al., 2018) to physical and mental health declines (Wang et al., 2017; Xue et al., 2019). With improving energy efficiency becoming a top priority (Shan et al., 2017), China has launched a series of regulations that propose significant goals for future energy intensity (Zhang et al., 2017), such as the Energy Development Strategic Action Plan, the U.S.-China Joint Presidential Statement on Climate Change, Made in China 2025, and the "Five-Year Plan" (FYP). Effective progress has been made toward achieving these targets: According to the International Energy Agency's (2018) report *Energy Efficiency 2018*, the worldwide movement of economic activities away from energy-intensive industrial sectors has offset a more than 25% increase in final energy use, 40% of which was due to China's contribution.

Writing – review & editing: Shuai Shao, Shiyi Chen, Jinyue Yan, Yuli Shan, Zhu Liu, Dabo Guan

While setting significant energy-saving targets for the whole country, China also allocated different energy-saving quotas in different provinces, which resulted in increasing disparities in energy intensity. The primary energy consumption of seven more developed provinces declined initially from 2011 to 2016, while the total primary energy consumption still increased at a rate of 3.46% (Ou et al., 2019). Under the 12th FYP (a series of social and economic development initiatives implemented during 2010–2014), the regional allocation of energy intensity is based on the "common but differentiated" burden sharing rules (Ringius et al., 1998) and is quite diverse across provinces according to their economic development levels (Dong et al., 2018; Yi et al., 2011): Xinjiang, Tibet, and Qinghai, some of the least developed and least energy-saving provinces in China, are required to cut their energy intensity by 10%, while Tianjin, Shanghai, Jiangsu, Zhejiang, and Guangdong, some of the most developed and most energy-saving provinces, are required to cut their energy intensity by 18%. Since energy intensity targets are not allocated equally across regions, they may have triggered traditional manufacturing transfer and amplified the energy intensity gap between different regions. This primary energy intensity gap may hinder the achievement of a country's energy intensity target (Burnett & Madariaga, 2017), given that some regions' energy-saving potential is not fully exploited through technological spillovers and interregional cooperation (Alcantara & Duro, 2004; De Groot & Mulder, 2012).

The disparity in China's energy intensity receives much research attention. For example, Zhang et al. (2011) and Jiang et al. (2017) analyzed that per capita energy use and energy intensity are higher in Middle and West China. Jiang et al. (2018) applied convergence analysis to prove the interregional spillover effect of energy intensity. The reasons for this interregional gap in energy consumption and energy efficiency include technology heterogeneity (Zhang & Zhou, 2020), energy consumption structure (Wu, 2012), the development of heavy industries (Jiang et al., 2014; Li et al., 2013), and urbanization (Ma, 2015). Using multiregional input-output (MRIO) analysis, several studies have also shown more energy embodied products are exported from West China to East China, accounting for enlarging disparities in energy intensity (Sun et al., 2017; Zhang et al., 2016). Based on the significant interregional disparities in energy intensity, Dong et al. (2018) divided China into three regions and analyzed the energy conservation potential for each of the three regions in 2030.

However, most of the abovementioned studies aimed to investigate the spatial relationship between different regions, instead of comprehensively revealing the extents of interregional disparities, or the contribution of different regions and factors to the disparities. In this paper, we use the Zenga inequality index to comprehensively measure the extent of interregional disparities. Based on the upper and lower arithmetic means of each point of the distribution, one of the main advantages of the Zenga index is that it can be used to reveal the contribution of each observation sample to the overall disparities (Grossi & Mussini, 2017; Wang et al., 2020). Moreover, this paper combines the Zenga index with the index decomposition analysis method proposed by Ang (2004) and Wang and Zhou (2018) and proposes a novel and systematic method to decompose the Zenga index into multiple multiplicative and additive contributors. To the best of our knowledge, this is the first study that proposes such a systematic method to decompose the Zenga index. Therefore, using the Zenga inequality index helps us not only to understand the interregional difference in energy intensity within China more comprehensively but also to offer differentiated emission-reduction strategies according to each region's development status. We also present the measurement of disparity in energy intensity in China using the Theil index, the Gini index, and the coefficient of variation (CV), which all yield similar results and help prove the durative spatial separation of energy-producing activities and final energy-consuming activities in China.

We first characterize China's disparities in energy intensity by adopting provincial annual data from the China Energy Statistical Yearbook (1996–2018), the Zenga inequality index, and the Theil inequality index, to decompose the drivers for disparities in energy intensity in terms of provinces, regions, energy transformation, energy consumption structure, sectoral energy intensity, and sectoral structure. The results provide in-depth insights into the present situation, potential causes, and future evolution of disparity and polarization in energy intensity in China. Finally, we conclude that the ongoing regional development plans should be more reconciled with energy conservation and the development of renewable energy and green technology.

2. Materials and Methods

2.1. Measuring China's Interprovincial Energy Intensity Disparity

We adopt the Zenga inequality index (Zenga, 2007) to calculate China's interprovincial disparities in primary and final energy intensities, which can measure disparity at various points of the distribution and reflect specific province's contribution to the overall disparity. The primary energy intensity of province h can be decomposed to the product of the energy transformation rate and final energy intensity as follows:

$$p_h = \frac{PE_h}{GDP_h} = \frac{PE_h}{FE_h} \cdot \frac{FE_h}{GDP_h} = t_h \cdot f_h \tag{1}$$

where p_h, t_h, and f_h are the primary energy intensity, energy transformation rate, and final energy intensity of province h, respectively; PE_h, FE_h, and GDP_h are primary energy consumption, final energy consumption, and gross domestic product (GDP) of province h, respectively. Mathematically, the Zenga inequality index is based on the weighted ratio of the upper and lower arithmetic means. Thus, we sort the primary energy intensity p_h in ascending order and set the province with the highest primary energy intensity as province r, and the upper and lower arithmetic means of the primary energy intensities can be calculated as follows, respectively:

$$M_h^-(p) = \frac{\sum_{j=1}^{h} PE_j}{\sum_{j=1}^{h} GDP_j} = \frac{\sum_{j=1}^{h} PE_j}{\sum_{j=1}^{h} FE_j} \cdot \frac{\sum_{j=1}^{h} FE_j}{\sum_{j=1}^{h} GDP_j} = M_h^-(t) M_h^-(f) \tag{2}$$

$$M_h^+(p) = \begin{cases} \dfrac{\sum_{j=h+1}^{r} PE_j}{\sum_{j=h+1}^{r} GDP_j} = \dfrac{\sum_{j=h+1}^{r} PE_j}{\sum_{j=h+1}^{r} FE_j} \cdot \dfrac{\sum_{j=h+1}^{r} FE_j}{\sum_{j=h+1}^{r} GDP_j} = M_h^+(t) M_h^+(f), & h \leq r-1 \\[2mm] \dfrac{PE_r}{GDP_r} = \dfrac{PE_r}{FE_r} \cdot \dfrac{FE_r}{GDP_r} = M_r^+(t) M_r^+(f), & h = r. \end{cases} \tag{3}$$

where $M_h^-(p)$, $M_h^-(t)$, and $M_h^-(f)$ are the average primary energy intensity, energy transformation rate, and final energy intensity of provinces with primary energy intensities less than or equal to p_h, respectively; $M_h^+(p)$, $M_h^+(t)$, and $M_h^+(f)$ are the average primary energy intensity, energy transformation rate, and final energy intensity of provinces with primary energy intensities higher than p_h, respectively. Specifically, since province r is the province with the highest primary energy intensity, $M_r^+(t)$ and $M_r^+(f)$ are equal to the energy transformation rate and final energy intensity of province r, respectively. The primary energy intensity disparity at each point of the distribution can be evaluated by the relative gap between the higher arithmetic mean of primary energy intensity $M_h^+(p)$ and lower arithmetic mean of primary energy intensity $M_h^-(p)$ as follows:

$$\begin{aligned} I_h(p) &= \frac{M_h^+(p) - M_h^-(p)}{M_h^+(p)} = \frac{M_h^+(t) M_h^+(f) - M_h^-(t) M_h^-(f)}{M_h^+(p)} \\[2mm] &= \frac{\left[M_h^+(t) - M_h^-(t) \right] \cdot M_h^-(f)}{M_h^+(p)} + \frac{\left[M_h^+(f) - M_h^-(f) \right] \cdot M_h^-(t)}{M_h^+(p)} \\[2mm] &\quad + \frac{\left[M_h^+(t) - M_h^-(t) \right] \cdot \left[M_h^+(f) - M_h^-(f) \right]}{M_h^+(p)} = I_h^t(p) + I_h^f(p) + I_h^{int}(p) \end{aligned} \tag{4}$$

where $I_h(p)$ is the relative gap in primary energy intensity between the bottom h provinces and the top r-h provinces. It can be decomposed into the disparity in final energy intensity, the disparity in energy transformation rate, and their cross-multiplication term, denoted as $I_h^t(p)$, $I_h^f(p)$, and $I_h^{int}(p)$, respectively. The overall disparity in primary energy intensity, and its driving factors from the disparity in energy transformation rate, the disparity in final energy intensity, and the interaction between energy transformation rate

and final energy intensity are the means of $I_h(p)$, $I_h^t(p)$, $I_h^f(p)$, and $I_h^{int}(p)$ weighted by GDP as follows, respectively:

$$I(p) = \sum_{h=1}^{r} I_h(p) \cdot \frac{GDP_h}{\sum_{h=1}^{r} GDP_h} \tag{5}$$

$$I^t(p) = \sum_{h=1}^{r} I_h^t(p) \cdot \frac{GDP_h}{\sum_{h=1}^{r} GDP_h} \tag{6}$$

$$I^f(p) = \sum_{h=1}^{r} I_h^f(p) \cdot \frac{GDP_h}{\sum_{h=1}^{r} GDP_h} \tag{7}$$

$$I^{int}(p) = \sum_{h=1}^{r} I_h^{int}(p) \cdot \frac{GDP_h}{\sum_{h=1}^{r} GDP_h} \tag{8}$$

As a robustness check, we also decompose the disparity in primary energy intensity using the Theil index. According to Duro et al. (2010) and Duro and Padilla (2011), we first calculate two hypothetical vectors of primary energy consumption per unit of GDP and let the value of each factor included in Equation 1 diverge from the mean as follows, respectively:

$$p_h^t = t_h \cdot \overline{f} \tag{9}$$

$$p_h^f = \overline{t} \cdot f_h \tag{10}$$

where $\overline{f}$ and $\overline{t}$ are the national averages of final energy intensity and energy transformation rate, respectively. According to Duro and Padilla (2006), the Theil index, denoted as $T(\cdot)$, allows a synthetic decomposition of national primary energy intensity disparity into three factors as follows:

$$T(p, y) = T(p^t, y) + T(p^f, y) + \log\left(1 + \frac{\sigma_{t,f}}{\overline{p}}\right) = T_t + T_f + inter_{t,f} \tag{11}$$

where T_t, T_f, and $inter_{t,f}$ are the disparity in energy transformation rate, the disparity in final energy intensity, and their interaction term, respectively. $\sigma_{t,f}$ is the covariance between energy transformation rate and final energy intensity; $\overline{p}$ is the national average of $p_h t$; and y is the GDP share of province h in the national GDP.

We observe that the change direction of the Theil index is generally similar with that of the Zenga index. Due to limited space, the decomposition results are plotted in supporting information Figure S1 and also listed in our Data Set S1.

2.2. Measuring Drivers of the Disparity in Energy Intensity

Here we apply a different data set on energy inventory compiled by Shan, Guan, Zheng, et al. (2018) and Shan et al. (2020), to more rigorously identify the influences of energy consumption structure, sectoral energy intensity, and sectoral structure on the disparity in energy intensity. First, we sort the energy intensity e_h in ascending order and let $M_h^-(e)$ be the average energy intensity of provinces with energy intensities less than or equal to e_h. Thus, $M_h^-(e)$ can be further decomposed as follows:

$$M_h^-(e) = \sum_j \sum_k \frac{M_{hjk}^-(E)}{M_{hj}^-(E)} \frac{M_{hj}^-(E)}{M_{hj}^-(Y)} \frac{M_{hj}^-(Y)}{M_h^-(Y)} = \sum_j \sum_k M_{hjk}^-(es) M_{hj}^-(ei) M_{hj}^-(ss) \tag{12}$$

where $M_{hjk}^-(E)$, $M_{hj}^-(E)$, $M_{hj}^-(Y)$, and $M_h^-(Y)$ denote the consumption of energy source k in sector j, the total energy consumption of sector j, the value added of sector j, and the total value added in provinces with energy intensities lower than or equal to e_h, respectively. Their multiplication can be transformed into the multiplication of $M_{hjk}^-(es)$ (the energy consumption structure of energy source k in sector j), $M_{hj}^-(ei)$ (the energy

Table 1
Data Structure of Primary Energy Intensity of k Subgroups

Primary energy intensity	Subgroups					Total
	1	...	g	...	k	
p_1	n_{11}	...	n_{1g}	...	n_{1k}	$n_{1\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
p_h	n_{h1}	...	n_{hg}	...	n_{hk}	$n_{h\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
p_r	n_{r1}	...	n_{rg}	...	n_{rk}	$n_{r\bullet}$
Total	$n_{\bullet 1}$	...	$n_{\bullet g}$	...	$n_{\bullet k}$	N

Note. Primary energy intensity p_h is sorted in ascending order.

intensity of sector j), and $M_{hj}^-(ss)$ (the sectoral structure of sector j) in provinces with energy intensities less than or equal to e_h.

Aligned with $M_h^-(e)$, $M_h^+(e)$ can also be decomposed into the following multiplied terms:

$$M_h^+(e) = \sum_j \sum_k \frac{M_{hjk}^+(E)}{M_{hj}^+(E)} \frac{M_{hj}^+(E)}{M_{hj}^+(Y)} \frac{M_{hj}^+(Y)}{M_h^+(Y)} = \sum_j \sum_k M_{hjk}^+(es) M_{hj}^+(ei) M_{hj}^+(ss) \tag{13}$$

Then, we can decompose $M_h^+(e) - M_h^-(e)$ using the index decomposition analysis method proposed by Ang (2004) as follows:

$$M_h^+(e) - M_h^-(e) = \sum_j \sum_k L\left(w_{hjk}^+, w_{hjk}^-\right) \ln\left(\frac{M_{hjk}^+(es)}{M_{hjk}^-(es)}\right) + \sum_j \sum_k L\left(w_{hjk}^+, w_{hjk}^-\right) \ln\left(\frac{M_{hj}^+(ei)}{M_{hj}^-(ei)}\right)$$
$$+ \sum_j \sum_k L\left(w_{hjk}^+, w_{hjk}^-\right) \ln\left(\frac{M_{hj}^+(ss)}{M_{hj}^-(ss)}\right) = \sum_j \sum_k \Delta_{hjk} es + \sum_j \Delta_{hj} ei + \sum_j \Delta_{hj} ss \tag{14}$$

where $L\left(w_{hjk}^+, w_{hjk}^-\right) = \dfrac{\dfrac{M_{hjk}^+(E)}{M_h^+(Y)} - \dfrac{M_{hjk}^-(E)}{M_h^-(Y)}}{\ln\dfrac{M_{hjk}^+(E)}{M_h^+(Y)} - \ln\dfrac{M_{hjk}^-(E)}{M_h^-(Y)}}.$

We can insert the decomposed $M_h^+(e) - M_h^-(e)$ into Equations 15–17 to retrieve the drivers of the disparity in energy intensity from the perspectives of energy consumption structure $I_k^{es}(e)$, sectoral energy intensity $I_j^{ei}(e)$, and sectoral structure $I_j^{ss}(e)$, as follows:

$$I_k^{es}(e) = \sum_h \left(\frac{\sum_j \Delta_{hjk} es}{M_h^+(e)} \cdot \frac{GDP_h}{\sum_{h=1}^r GDP_h} \right) \tag{15}$$

$$I_j^{ei}(e) = \sum_h \left(\frac{\Delta_{hj} ei}{M_h^+(e)} \cdot \frac{GDP_h}{\sum_{h=1}^r GDP_h} \right) \tag{16}$$

$$I_j^{ss}(e) = \sum_h \left(\frac{\Delta_{hj} ss}{M_h^+(e)} \cdot \frac{GDP_h}{\sum_{h=1}^r GDP_h} \right) \tag{17}$$

2.3. Decomposing Into Within-Group and Between-Group Components and Evaluating Polarization

2.3.1. Evaluating Polarization With Exogenous Groups

The Zenga inequality index has the high quality of additive decomposability (Radaelli, 2010) and can be decomposed into the sum of the within-group disparity and the between-group disparity without redundant terms. Here we divide r provinces in China into k subgroups ($k = 3$ in our case) and set their GDP and primary energy intensity as $y_1, y_2, ..., y_r$ and $p_1, p_2, ..., p_r$ respectively. In addition, n_{hg} denotes the GDP of province h if province h is within subgroup g as follows:

$$n_{hg} = \begin{cases} y_h, & \text{if province } h \text{ is included in subgroup } g \\ 0, & \text{if province } h \text{ is not included in subgroup } g \end{cases} \tag{18}$$

The data structure is shown in Table 1.

Thus, we have

$$\sum_{g=1}^{k} n_{\bullet g} = \sum_{h=1}^{r} n_{h \bullet} = N \tag{19}$$

$$\sum_{h=1}^{r} n_{hg} = n_{\bullet g} \tag{20}$$

$$\sum_{g=1}^{k} n_{hg} = n_{h \bullet} \tag{21}$$

The Zenga inequality index for the disparity in primary energy intensity can be decomposed into within-group component $I^w(p)$ and between-group component $I^b(p)$ as follows:

$$I(p) = I^w(p) + I^b(p) \tag{22}$$

$$I^w(p) = \sum_{l=1}^{k} \left\{ \sum_{h=1}^{r} \left[\frac{M_{hl}^+(p) - M_{hl}^-(p)}{M_{h \bullet}^+(p)} \right] b(l|h) u(l|h) \frac{n_{h \bullet}}{N} \right\} \tag{23}$$

$$I^b(p) = \sum_{l=1}^{k} \sum_{g:g \neq l} \left\{ \sum_{h=1}^{r} \left[\frac{M_{hg}^+(p) - M_{hl}^-(p)}{M_{h \bullet}^+(p)} \right] b(l|h) u(g|h) \frac{n_{h \bullet}}{N} \right\} \tag{24}$$

In these equations, $M_{hl}^+(p)$ and $M_{hl}^-(p)$ are higher and lower average primary energy intensities for subgroup l, respectively, and $M_{h \bullet}^+(p)$ is the higher average energy intensity in all subgroups. Variable $b(l|h) = P_{hl}/P_{h \bullet}$ represents the relative GDP of subgroup l to all subgroups with lower energy intensities than p_h, where P_{hl} denotes summed GDP for provinces with energy intensities lower than or equal to p_h in subgroup l and $P_{h \bullet}$ stands for summed GDP for provinces with energy intensities less than or equal to p_h in all subgroups. Variable $u(l|h)$ represents the relative GDP of subgroup l to all subgroups with higher energy intensities. When $h = r$, $u(l|h) = n_{rl}/n_{r \bullet}$; when $h = 1, 2, ..., r-1$, $u(l|h) = (n_{\bullet l} - P_{hl})/(n - P_{h \bullet})$.

The magnitude of polarization reveals the convergence of energy intensity within each exogenous grouped region and divergence of primary energy intensity between the grouped regions. The polarization index can be measured by the comparison between within-group component $I^w(p)$ and between-group component $I^b(p)$. According to Zhang and Kanbur (2001), we adopt the Z-K index to construct the energy intensity polarization index as follows:

$$Z\text{-}K = \frac{I^b(p)}{I^w(p)} \tag{25}$$

The Z-K index being greater than 1 indicates a strong multipolarization of the tested sample.

2.3.2. Evaluating Polarization With Endogenous Groups

An alternative way to evaluate polarization is to apply the endogenous grouping standards, in which groups are formed optimally to minimize concealed energy intensity gap (Aghevli & Mehran, 1981). We use the EGR index proposed by Esteban et al. (2007) to measure the polarization in energy intensity with endogenous groups as follows (Duro & Padilla, 2013):

$$EGR(\alpha, \beta) = \sum_{i=1}^{r} \sum_{j=1}^{r} \left[\left(\frac{y_i}{\sum y_i} \right)^{1+\alpha} \frac{y_j}{\sum y_j} \left| \frac{p_i}{\bar{p}} - \frac{p_j}{\bar{p}} \right| \right] - \beta(G - G_b) = ER - \varepsilon \tag{26}$$

where $\frac{y_i}{\sum y_i}$ and $\frac{y_j}{\sum y_j}$ are the GDP proportions of regions i and j, respectively; p_i and p_j are the primary energy intensities of regions i and j, respectively; $\bar{p}$ is the average primary energy intensity of China; α and β are the parameters that measure the sensitivity of the index to polarization; G is the Gini index of the observation sample; and G_b is the between-group Gini index measuring between-group inequality. The measure has two parts, which are the ER index (proposed by Esteban and Ray, 1994, and denoted as ER in

this study) and the error term (denoted as ε). *ER* is axiomatically derived using a behavioral model and is formally defined as follows:

$$ER = \sum_{i=1}^{r} \sum_{j=1}^{r} \left[\left(\frac{y_i}{\sum y_i} \right)^{1+\alpha} \frac{y_j}{\sum y_j} \left| \frac{p_i}{\bar{p}} - \frac{p_j}{\bar{p}} \right| \right] \tag{27}$$

ε is a measurement of between-group inequality and is defined as follows:

$$\varepsilon = \beta(G - G_b). \tag{28}$$

Following Duro (2005), we set $\alpha = 1$ or 1.3, and $\beta = 1$. Aligned with the number of exogenous groups, we set the number of endogenous groups as 3 and use the endogenous grouping algorithms proposed by Davies and Shorrocks (1989), in which the loss of distributional detail is minimized.

2.4. Test for Significant Difference in the Z-K and EGR Indexes

We model the Z-K and EGR indexes as a function of a dummy variable denoting whether the polarization index is measured within the *i*th FYP period as follows:

$$POL_t = \alpha_0^i + \alpha_1^i D_t^i \tag{29}$$

where POL_t denotes the polarization index at period t and D_t^i denotes if t belongs to the *i*th FYP period. D_t^i equals to 1 if t belongs to the *i*th FYP period and equals to 0 otherwise. In order to show if there exists a significant change in the Z-K and EGR indexes in each FYP period, we run the model for eight times and let $i = 8, 9, 10, 11, 12,$ and 13.

2.5. Data

The data collected initially in this study concern provincial primary and final energy consumption (physical units), which are from provincial energy balance sheets in the *China Energy Statistical Yearbook* (1996–2018). Since provincial energy balance sheets do not include information on energy consumption in very specific industries, we also use energy inventories compiled by Shan, Guan, Zheng, et al. (2018) and Shan et al. (2020) to more rigorously decompose the drivers of the disparity in energy intensity. We convert these data into coal equivalent using conversion factors (see Table S1) from related yearbooks.

3. Results

3.1. Evolution of Disparity and Polarization in Energy Intensity

Here we evaluate the interprovincial disparity in primary energy intensity adopting the Zenga inequality index and decompose it into three components: the disparity in final energy intensity, the disparity in energy transformation rate, and the interaction between disparities in final energy intensity and energy transformation rate. The disparity in primary energy intensity and its decomposition, along with the temporal evolution of energy intensity, are depicted in Figure 1.

Figure 1 clearly demonstrates that the growth trend of energy consumption in China corresponds with the national economic, energy, and environmental policies. Primary energy consumption started to surge in 2002, when China joined the World Trade Organization (WTO) and advocated developing an open economic system and expanding manufacturing, with an 11.87% growth rate of primary energy consumption on average from 2002 to 2009. However, in late 2009, with the targets and actions pledged under the Copenhagen Accord, the Chinese government committed to enhancing energy conservation and allocated this target to the provincial level. This energy-saving trajectory has been effective since the growth of China's primary and final energy consumption has slowed down: From 2010 to 2017, primary and final energy consumption increased by only 5.53% and 4.51% per year, on average, respectively.

However, at the same time, we find that the interprovincial gap in primary energy intensity (plotted as columns, sum of disparity in final energy intensity, disparity in energy transformation, and their interaction) is rising, while the growth of energy intensity is slowing down. Before 2007, the disparity in energy intensity within China remained below 0.62 in all years. In contrast, after 2008, disparity in primary energy intensity is generally higher and fluctuates with an average of 0.6749.
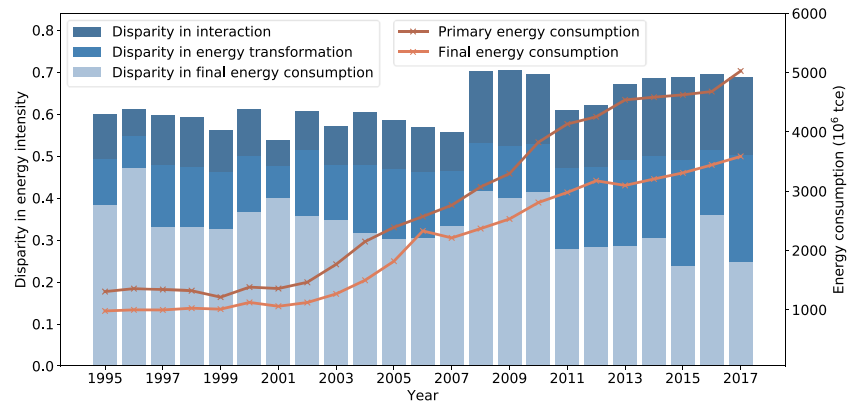
Figure 1. Evolution of disparity in energy intensity and energy consumption. Interaction in the legend denotes the interaction between energy transformation rate and final energy intensity disparities. Total disparity in energy intensity is plotted as the columns (sum of disparity in energy transformation rate, disparity in final energy intensity, and their interaction).

The main contributor to the disparity in primary energy intensity is the disparity in final energy intensity, contributing for 47.59% on average, although its influence has shrunk from 63.69% in 1995 to 35.73% in 2017. Meanwhile, the contribution of the disparity in energy transformation rate increased to 37.28% in 2017. The energy transformation rate is expressed as the quotient of primary energy consumption and final energy consumption, which is inversely proportional to the energy transformation efficiency. The enlarging gap between provincial primary and final energy consumption indicates unequal interprovincial energy transfer and diverse energy conversion technology during transformation (Shan, Guan, Hubacek, et al., 2018).

The interaction between final energy intensity and the energy transformation rate is always positive, indicating that provinces with higher final energy intensities tend to have lower energy transformation efficiency. This is because primary energy produced by provinces with the highest energy intensities is usually transferred to and consumed by provinces with lower energy intensities. For instance, about 20% of the coal used in the Jing-Jin-Ji region, a city cluster with relatively low energy intensity in China, is produced by the nearby provinces with higher energy intensities, Shanxi and Inner Mongolia (Shan, Guan, Zheng, et al., 2018).

Figure 2 shows the distribution of primary and final energy intensity in different years (GDP deflated to 1995) and verifies the Zenga inequality index in energy intensity in Figure 1 mutually. Figure 2a reveals that
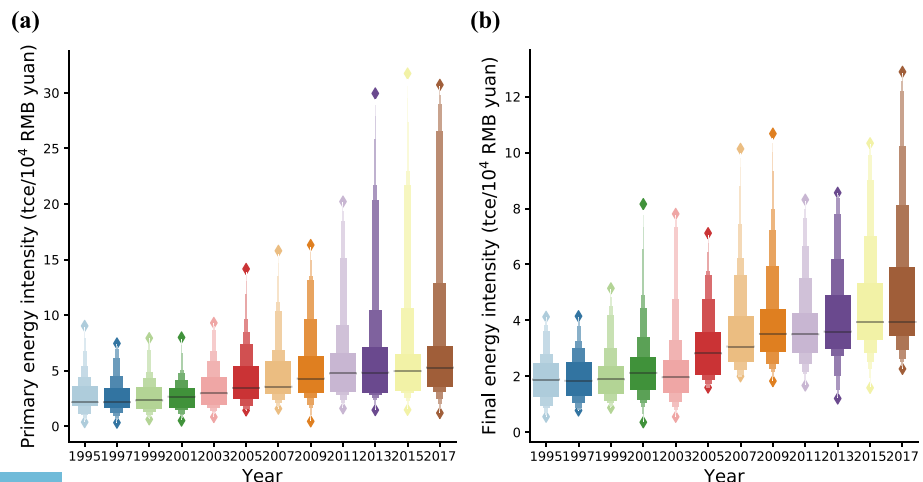

Figure 2. Energy intensity distribution. (a) Primary energy intensity distribution. (b) Final energy intensity distribution.
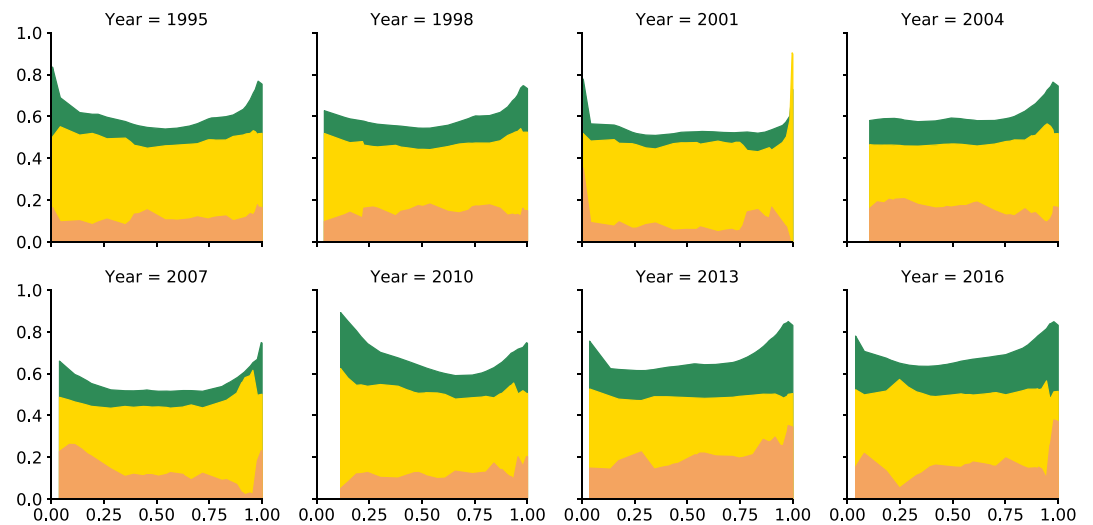
Figure 3. Disparity curve of energy intensity of selected years. The contribution of energy transformation rate (brown), final energy intensity (yellow), and their interaction (green) to disparity in primary energy intensity in different provinces. The *x*-axis denotes the accumulated share of provincial GDP ordered in ascending primary energy intensity.

while the lowest level of primary energy intensity among the 30 provinces remains almost the same, the highest level of primary energy intensity increases from 9.04 to 30.72 tonnes of coal equivalent (tce) per 10^4 Renminbi (RMB) yuan at the 1995 constant price from 1995 to 2017. The disparity in final energy intensity is also increasing but with a much smaller extent. The difference between the highest and lowest final energy intensities increased from 3.57 tce per 10^4 RMB in 1995 to 10.06 tce per 10^4 RMB in 2009 and 10.62 tce per million RMB in 2017.

One of the most obvious advantages of the Zenga inequality index is that it can clearly show which part in the distribution contributes most to the overall disparity (Langel & Tillé, 2012; Pasquazzi & Zenga, 2018). We create disparity curves of energy intensity from 1995 to 2017 to show this property. Since the shape of the disparity curves of energy intensity is similar in adjacent years, only 1 in 3 years is shown in this paper (Figure 3). The *x*-axis denotes the accumulated share of provincial GDP ordered in ascending primary energy intensity. The contribution of the energy transformation rate, final energy intensity, and their interaction to disparity in primary energy intensity is almost unchanged in the early years. However, in recent years, disparities in the energy transformation rate and the interaction between the energy transformation rate and final energy intensity play a greater part in the disparity in primary energy intensity (shown as year = 2013 and year = 2016 in Figure 3). We can intuitively see that energy intensity in China is strongly polarized. The left and right ends of each of the disparity curve are rising, indicating provinces with the highest and lowest primary energy intensities contribute more to the disparity in energy intensity. Simultaneously, provinces with moderate energy intensity levels contribute less than those at the bottom and the top. The disparity curves in 2013 and 2016 rise as the accumulated share of provincial GDP approaches 1. This shows that the provinces with the highest energy intensities, such as Gansu, Qinghai, Shanxi, Shaanxi, and Guizhou, have less advanced green technology and bear more heavy industrial transfer from other more developed provinces.

3.2. Multipolarization Trend of Energy Intensity

Polarization is a relative but distinctive concept from disparity and inequality (Autor et al., 2008; Motiram & Sarma, 2014). Knowledge of energy intensity polarization is very effective in guiding reductions agreements and mitigating potential instability (Duro, 2015). Figure 4 presents the kernel density estimation of the distribution of energy intensity in China during 1995–2017. We sample data with weights in a normal distribution (i.e., using normal kernel), and the optimal bandwidth is selected through a data-driven method that maximizes the log likelihood with the leave-one-out cross-validation. We find that the distribution of energy intensity in China in most years is unimodal and positively skewed, implying that the bulk of regions have relatively lower energy intensities. Over our research period, the mode and the peak of primary energy
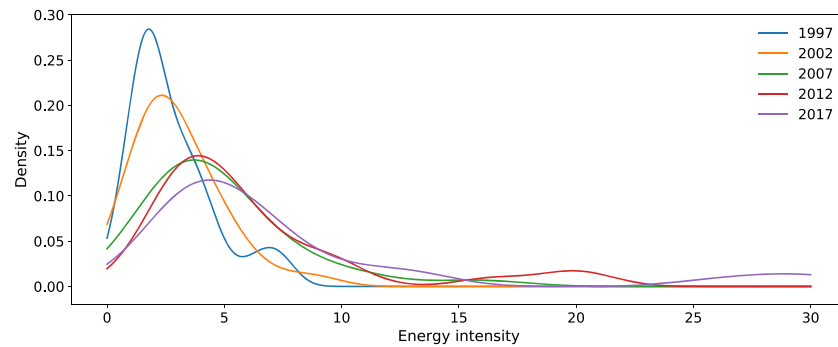
Figure 4. Kernel density estimation of the distribution of energy intensity in China.

intensity increasingly become higher and lower, respectively, indicating that primary energy intensities in most regions get higher and more dispersed. Moreover, the characteristic of heavy-tailed distribution is observed in 2012 and 2017. Specifically, in these 2 years, the energy intensities of some provinces reached an unprecedented level, with the highest primary energy intensities reaching 20 tce per 10^4 RMB and 30 tce per 10^4 RMB, respectively.

Polarization in energy intensity can also be evaluated quantitatively. According to Zhang and Kanbur (2001), the energy intensity polarization can be evaluated as the quotient of the sum of between-group energy intensity disparity and the sum of within-group energy intensity disparity. We divide China into three economic regions according to exogenous geographical factors (the East, the Middle, and the West; see Figure S2), to construct the between-group and within-group Zenga inequality indexes (see Table 2). We find that our geographically based region classification can explain around 70% of the disparity in energy intensity, indicating that our classification criteria capture the essential characteristics of the polarization in primary energy intensity within China.

Furthermore, we sort China's provinces into three endogenous groups and measure the polarization with the EGR index (see Table 3). The FYP in China is a series of economic, environmental, and social development guidelines issued once in 5 years, which provides the predominant development targets in China. Considering that China's targets and efforts in mitigating energy consumption vary a lot during different FYP periods, we further divide our whole evaluated period into six FYP periods, measure the average Z-K and EGR indexes during each FYP period, and use an ordinary least squares regression model to test whether the Z-K and EGR indexes during each FYP period is significantly different.

From the decomposition results, we observe that the polarization indexes evolve in the same direction as the inequality indexes. This implies that the distribution of primary energy intensity centralizing around distant poles is a substantial contributor for enlarging disparities. During every FYP period, the average Z-K index is higher than 2.0, validating our observation in Figure 4 that provincial energy intensities within China are strongly polarized. The provincial energy intensity gaps between the East and the Middle (Between 1 & 2), between the East and the West (Between 1 & 3), and within the East (Within 1) are the largest during most

Table 2
Z-K Index Within China During Six FYP Periods

FYP	Period	$I(E)$	Between 1 and 2	Between 1 and 3	Between 2 and 3	Within 1	Within 2	Within 3	Z-K index
8th	1995	0.5988	0.2222	0.1481	0.0488	0.1307	0.0304	0.0187	2.3309
9th	1996–2000	0.5911	0.1859	0.1784	0.0527	0.1241	0.0273	0.0228	2.4463
10th	2001–2005	0.5806	0.1378	0.1673	0.0558	0.1381	0.0275	0.0252	2.0485**
11th	2006–2010	0.6446	0.1071	0.2192	0.1108	0.1025	0.0197	0.0853	2.1024*
12th	2011–2015	0.6538	0.1969	0.2072	0.0785	0.0966	0.0463	0.0283	2.8267***
13th	2016–2017	0.6935	0.2147	0.2130	0.0747	0.1186	0.0482	0.0244	2.6278

Note. "Between" and "Within" denote between-group disparity and within-group disparity, respectively. Numbers 1, 2, and 3 denote three exogenous groups (the East, the Middle, and the West, respectively; see Figure S1). The whole results for the Z-K index are displayed in Table S1.
*The Z-K index during this FYP period is statistically different at the significance level of 10%. **The Z-K index during this FYP period is statistically different at the significance level of 5%. ***The Z-K index during this FYP period is statistically different at the significance level of 1%.

Table 3
EGR Index Within China During Six FYP Periods

FYP	Period	$\alpha = 1$			$\alpha = 1.3$		
		ER	ε	EGR	ER	ε	EGR
8th	1995	0.5656	0.2662	0.2994	0.2133	0.2662	−0.0530
9th	1996–2000	0.5600	0.2820	0.2779[*]	0.2111	0.2820	−0.0709[**]
10th	2001–2005	0.5458	0.2508	0.2950	0.2083	0.2508	−0.04249
11th	2006–2010	0.6166	0.2618	0.3548	0.2364	0.2618	−0.02533
12th	2011–2015	0.6834	0.2625	0.4209[**]	0.2519	0.2625	−0.01061
13th	2016–2017	0.7523	0.2616	0.4907[**]	0.2777	0.2616	0.0161[*]

Note. The EGR index of each year is displayed in Data Set S1.
[*]The EGR index during these FYP periods is statistically different at the significance level of 10%. [**]The EGR index during these FYP periods is statistically different at the significance level of 5%. [***]The EGR index during these FYP periods is statistically different at the significance level of 1%.

FYP periods, showing that provincial energy intensities in the East are generally lower than those of the Middle and the West, but still quite diversified. The EGR index also indicates that the polarization in energy intensity in China is generally getting higher and is mainly contributed by the increase in its component *ER*, while the value of component ε is relatively stable. Another interesting finding is that the Z-K and EGR indexes are relatively high during the 11th, 12th, and 13th FYP periods, when China attached importance to energy-saving and low-carbon development. The greatest and most significant decrease in the Z-K and EGR indexes occurred during the 9th and 10th FYP periods, respectively, when the central authorities transformed China's industrial sector into re-heavy-industrialization and set no official energy-saving target (Qi et al., 2013). The between-group disparity in energy intensity is relatively increasing, indicating that different economic zones are at different development stages; hence, economic activities and energy conservation actions are diverse across regions.

3.3. Driving Factors for Disparity in Energy Intensity

What are the possible causes of the disparity in energy intensity? Here we first adopt the Zenga inequality index to identify the contributions of energy consumption structure, sectoral energy intensity, and sectoral structure to the disparity in energy intensity in 1997 and 2016 (see Figure 5). The categorization of six sectors and five energy sources is shown in Tables S3 and S4. The results show that the discrepancy in energy-saving efforts, the differences in regional consumption of energy sources, energy efficiency, and economic structure greatly enlarge the regional gap in energy intensity. As the predominant energy for the West, coal consumption is one of the main factors driving up the disparity in energy intensity, and the impact of coal consumption increased in the last 20 years. However, due to lack of law and effective management, measures for mitigating coal consumption are currently limited (Guan et al., 2018). For instance, coal usage for heating during the winter is a great contribution of loose coal consumption in rural China (Tao et al., 2018) but is difficult to be tracked because of the geographically disperse consumption pattern of loose coal. On the other hand, energy sources more commonly used in the East (oil, natural gas, and nuclear and renewable energy) reduce the disparity, partly because their usage is more centralized and easier to be tracked and regulated. In addition, as China's oil, gas, and nuclear and renewable energy power industries are under administrative monopoly by the central government, these industries have more incentives to reinforce efforts to reduce environmental and climate change impacts of their products.

From the perspective of sectoral energy intensity, we find that the energy intensities of all the six sectors are higher in regions with higher energy intensities, which is the West in our case. Specifically, differences in energy intensity in heavy manufacturing sectors (denoted as heavy in Figure 5) contribute 49.69% and 69.46% to the disparity in regional energy intensity in 1997 and 2016, respectively, and differences in energy intensity in all the sectors account for more than 60% of the disparity in energy intensity in these 2 years. Thus, the enlarging disparity in energy intensity is indeed a problem of the enlarging disparity in regional energy processing efficiency. Furthermore, China's continuously increasing energy consumption may be exacerbated by the fact that regions with the most inferior energy processing technology are specified in energy-intensive production sectors. This indicates that energy sources are heavily misallocated across regions, and thus, energy-intensive industries prosper in regions with the lowest energy efficiencies. We
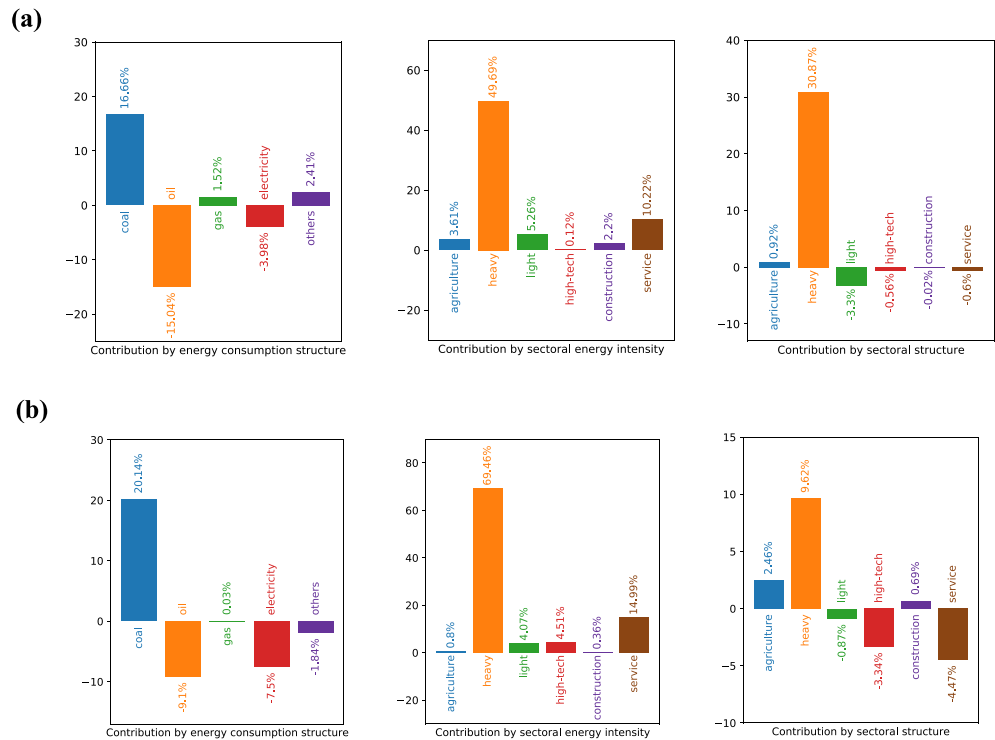
Figure 5. Driving factors of disparity in energy intensity (in percent of disparity in energy intensity). (a) Disparity contributed by energy consumption structure, energy intensity, and sectoral structure in 1997. (b) Disparity contributed by energy consumption structure, energy intensity, and sectoral structure in 2016

will soon discuss a source of the misallocation, which is a command-and-control energy policy that assigns different energy intensity reduction targets for different provinces.

From the perspective of sectoral structure, sectors that are the most conducive to the convergence in energy intensity are ones with relatively lower energy intensities, such as light manufacturing (denoted as light in Figure 5), high-tech manufacturing (denoted as high-tech in Figure 5), and service sectors. Meanwhile, agriculture and heavy manufacturing sectors have relatively higher energy intensities, thus prohibiting this convergence trend. The contribution of the disparity in sectoral structure to the disparity in energy intensity increasingly shrank in our research period, indicating that regional economic structure in China tended to be more coordinated.

The significantly enlarging disparities in the energy transformation rate are also due to frequent interregional energy flows within China, including both secondary energy trade (energy transfer between provinces) and cement product trade (nonenergy use). As the Middle and the West become specialized in heavy industries (Gasim, 2015), these regions become net exporters of embodied primary energy from interregional bilateral trade and may consume more energy producing these products. Evidence of the expanding interregional trade in energy consumption can be found in existing literature based on the MRIO model (Gao et al., 2018; Zhang et al., 2016). The use of MRIO analysis has proved that the interregional trade triggered energy consumption tripled at the national level between 2002 and 2007, with relatively large structural changes among regions.

The enlarging gap in energy intensity may also be due to a portfolio of energy-saving policies. Under the 12th FYP, China allocated different quotas to provinces in regard to cutting their energy consumption per GDP unit by 2015. The target and actual energy intensity reduction are shown in Figure 6. In this plan, provinces with the highest energy intensities, i.e., Gansu, Qinghai, Shanxi, Shaanxi, and Guizhou, are only regulated to cut their energy intensity by 16%, 15%, 16%, 15% and 10%, respectively, which are less stringent targets than those of provinces with lower energy intensities: The five provinces with the lowest energy intensities in 2010 all had an energy-saving target of 17% or higher. The only three provinces that failed to achieve their energy-saving goals, i.e., Guizhou, Ningxia, and Xinjiang, were all provinces with high energy intensities
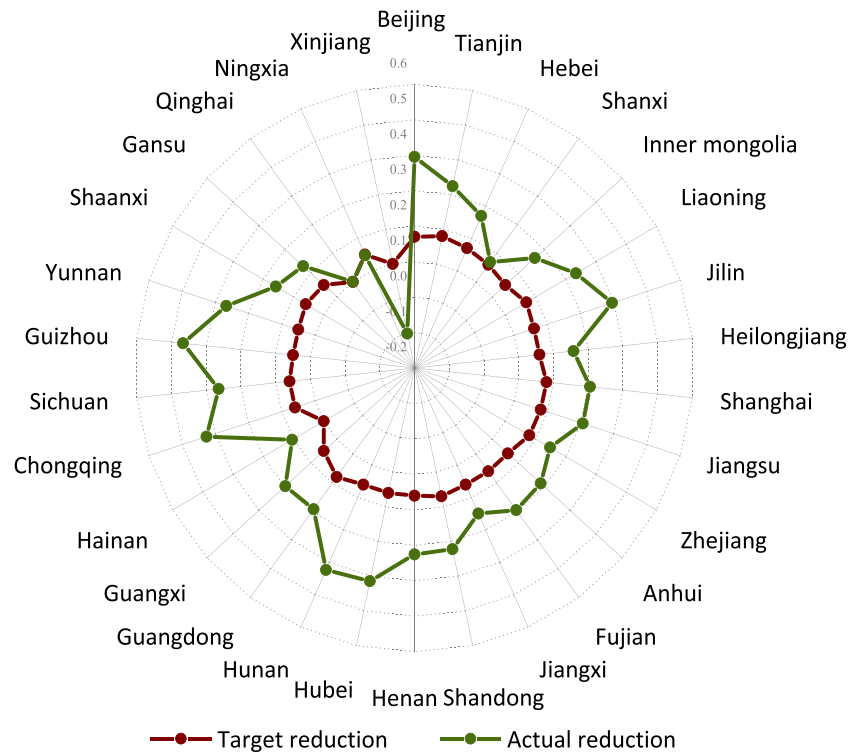
Figure 6. Energy intensity reduction (%) during the 12th FYP period. Provincial actual reduction (green, %) and target reduction (red, %) during the 12th FYP period.

located in western China. The regional allocation of energy intensity goals is now based on the "common but differentiated" burden sharing rules (Ringius et al., 1998). While the Middle and the West may have the obligation to save more energy due to their higher accumulated energy consumption in the past, they still need to focus on achieving economic development (Dong, Sun, et al., 2018; Yi et al., 2011). Due to energy technological progress and structural shifts toward the manufacturing of processed products (Organisation for Economic Co-operation and Development, 2012), the energy intensity in the East is controlled under the 12th FYP period, while the Middle and the West have undertaken energy-intensive industrial transfer from the East and focused more on economic development. Since the raw-material-intensive industrial transfer within China is untraceable because the enterprises may change their names and legal codes, we can only find news articles on industrial transfer: Many high-emission enterprises have been reported to relocate to the regions with lower energy-saving and environmental standards or to be shut down, due to stricter energy-saving requirements.

4. Discussion and Conclusion

In recent years, China's energy consumption has grown continuously, causing the contradiction between natural resources and economic growth to become increasingly prominent. Many measures are taken to reduce China's energy intensity, which have achieved remarkable results, but, at the same time, amplified disparity in energy intensity. United national energy intensity is largely hindered by provinces with the highest energy intensities. In 2017, on average, 31.18%, 31.63%, and 37.19% disparities in energy intensity are contributed by the least 10, middle 10, and top 10 energy-intensive provinces, respectively. What is more, the energy intensity gap is enlarging between different economic clubs. The disparity in energy intensity across the East, the Middle, and the West is almost three times as large as the disparity in energy intensity within these economic clubs, indicating that the energy intensity distribution in China is getting polarized.

The disparity in energy intensity is more and more contributed by the disparity in energy transformation rate. This reflects four facts: The first is rather loose regulatory measures on mitigating coal consumption. Our decomposition results reveal that the discrepancy in energy-saving efforts and the regional

consumption of different energy sources greatly enlarges the regional gap in energy intensity. The main driver of energy intensity disparity is coal consumption, while oil, natural gas, and electricity consumption are currently inhibiting this trend. However, as a main factor driving up the disparity in energy intensity, coal consumption has been underregulated, thus leading to a continuously high level of the disparity in energy intensity. The second is inferior energy processing technology in areas specializing in energy-intensive industries. From our decomposition results, the disparity in sectoral energy intensity accounts for more than 90% of the disparity in energy intensity. Furthermore, provinces with the highest energy intensities in China are generally in the West, which more relies on energy-intensive industries. This indicates that the command-and-control energy policies (such as unbalanced energy-saving goals in the FYP) in China cause the misallocation of production factors across regions, leading to continuously rising energy consumption and potential total factor productivity losses (Hsieh & Klenow, 2009). The third is increasing interregional energy fluxes embodied in trade. The significantly enlarging disparities in the energy transformation rate are due to frequent interregional secondary energy flows within China. The Middle and the West gradually become energy base in China and consume more energy for producing these products. Besides, the disparity in energy intensity is a result of increasing net embodied energy flows from the middle and western regions of China to the coastal regions through closer interregional trade in domestic supply chains. The fourth is separate jurisdictions at provincial administrative levels. Another plausible explanation for increasing disparity in energy intensity is the regionally unbalanced allocation of energy-saving goals in the FYP. The middle and western regions of China are less motivated to cut their energy intensities as these regions not only bear a lighter burden to reduce their energy intensities but also are located upstream in the domestic supply chain. The four factors mentioned above can synthetically intrigue unintended spillover effects, in which some energy-intensive and carbon-intensive enterprises relocate to the regions with severe energy problems and inferior green technologies (i.e., the Middle and the West in our case). In the short term, the disparity and polarization in energy intensity within China is very likely to continue to increase. According to the 13th FYP (2016–2020), carbon emission control for different provinces will still be categorized, which may lead to the gaps in energy intensity. The intention of categorized constraint is to promote economic growth and optimize resource allocation efficiency (Guo et al., 2017). However, as our study shows, this may also result in a rigescent energy consumption structure and heavy industry agglomeration in regions with less advanced green technologies, thus leading to disparity and polarization in energy intensity and resulting in an overall obstructive effect on energy saving.

Therefore, more attention should be paid to the balanced development of energy efficiency and structure across different regions, in order for low-carbon energy transitions and energy intensity convergence (Fang et al., 2019; Geels et al., 2017). First, regional development strategies should comprehend energy conservation and emission reduction and mix more efforts in green policy. The Middle and the West should adapt to local conditions and promote the upgrading of industrial structure, the optimization of the energy structure, and the synergy of interregional technological innovation. The East should promote energy processing technology spillovers, eliminate high-energy-consuming enterprises instead of transferring them, and develop clean and renewable energy sources (Kivimaa & Kern, 2016). In particular, the Carbon Emission Trading System and the Certified Emission Reduction scheme can be conducted more to promote clean energy use and energy processing technology spillover in less developed regions. Second, more market-based energy and environmental policies, e.g., financial support and carbon pricing, are needed to incentivize energy transformation toward clean and renewable energy. Unlike conventional energy, renewable energy is more available of local resources (Ma et al., 2009) and can be applied in final services directly without fuels or power generation, transport, and import. The command-and-control energy and environmental policies, on the other hand, should be used with caution. Third, consumption-based emission-reduction targets should be adopted. In consumption-based emission-reduction targets, the West are subsidized by final consumers in the East that have greater ability to pay. Therefore, the West can achieve low-carbon transition without undercutting their economic core. Ongoing work involves deeper research on the requirements for success in these pathways.

Data Availability Statement

All data sets are available online from China Emission Accounts and Datasets at http://www.ceads.net/ and China Statistical Yearbooks Database at http://tongji.oversea.cnki.net/oversea/engnavi/navidefault.aspx.

References

Aghevli, B. B., & Mehran, F. (1981). Optimal grouping of income distribution data. *Journal of the American Statistical Association*, *76*(373), 22–26.

Alcantara, V., & Duro, J. A. (2004). Inequality of energy intensities across OECD countries: A note. *Energy Policy*, *32*(11), 1257–1260.

Ang, B. W. (2004). Decomposition analysis for policymaking in energy: Which is the preferred method? *Energy Policy*, *32*(9), 1131–1139.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in US wage inequality: Revising the revisionists. *The Review of Economics and Statistics*, *90*(2), 300–323.

Bhattacharyya, S. C. (2011). *Energy economics: Concepts, issues, markets and governance*. United Kingdom: Springer.

Burnett, J. W., & Madariaga, J. (2017). The convergence of US state-level energy intensity. *Energy Economics*, *62*, 357–370.

Davies, J. B., & Shorrocks, A. F. (1989). Optimal grouping of income and wealth data. *Journal of Econometrics*, *42*(1), 97–108.

De Groot, H. L. F., & Mulder, P. (2012). Structural change and convergence of energy intensity across OECD countries. *Energy Economics*, *34*(6), 1910–1921.

Dong, F., Long, R., Yu, B., Wang, Y., Li, J., Wang, Y., et al. (2018). How can China allocate CO_2 reduction targets at the provincial level considering both equity and efficiency? Evidence from its Copenhagen Accord pledge. *Resources, Conservation and Recycling*, *130*, 31–43.

Dong, K., Sun, R., Hochman, G., & Li, H. (2018). Energy intensity and energy conservation potential in China: A regional comparison perspective. *Energy*, *155*, 782–795.

Duro, J. A. (2005). Another look to income polarization across countries. *Journal of Policy Modeling*, *27*(9), 1001–1007.

Duro, J. A. (2015). The international distribution of energy intensities: Some synthetic results. *Energy Policy*, *83*, 257–266.

Duro, J. A., Alcántara, V., & Padilla, E. (2010). International inequality in energy intensity levels and the role of production composition and energy efficiency: An analysis of OECD countries. *Ecological Economics*, *69*(12), 2468–2474.

Duro, J. A., & Padilla, E. (2006). International inequalities in per capita CO_2 emissions: A decomposition methodology by Kaya factors. *Energy Economics*, *28*(2), 170–187.

Duro, J. A., & Padilla, E. (2011). Inequality across countries in energy intensities: An analysis of the role of energy transformation and final energy consumption. *Energy Economics*, *33*(3), 474–479.

Duro, J. A., & Padilla, E. (2013). Cross-country polarisation in CO_2 emissions per capita in the European Union: changes and explanatory factors. *Environmental and Resource Economics*, *54*(4), 571–591.

Esteban, J. M., Gradín, C., & Ray, D. (2007). An extension of a measure of polarization, with an application to the income distribution of five OECD countries. *The Journal of Economic Inequality*, *5*(1), 1–19.

Esteban, J. M., & Ray, D. (1994). On the measurement of polarization. *Econometrica*, *62*(4), 819–851.

Fang, D., Chen, B., Hubacek, K., Ni, R., Chen, L. & Feng, K., et al. (2019). Clean air for some: Unintended spillover effects of regional air pollution policies. *Science Advances*, *5*(4), eaav4707.

Gao, C., Su, B., Sun, M., Zhang, X., & Zhang, Z. (2018). Interprovincial transfer of embodied primary energy in China: A complex network approach. *Applied Energy*, *215*, 792–807.

Gasim, A. A. (2015). The embodied energy in trade: What role does specialization play? *Energy Policy*, *86*, 186–197.

Geels, F. W., Sovacool, B. K., Schwanen, T., & Sorrell, S. (2017). Sociotechnical transitions for deep decarbonization. *Science*, *357*(6357), 1242–1244.

Grossi, L., & Mussini, M. (2017). Inequality in energy intensity in the EU-28: Evidence from a new decomposition method. *The Energy Journal*, *38*(4).

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.

Guo, W., Sun, T., & Dai, H. (2017). Efficiency allocation of provincial carbon reduction target in China's "13·5" period: Based on zero-sum-gains SBM model. *Sustainability*, *9*(2), 167.

Hsieh, C. T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, *124*(4), 1403–1448.

International Energy Agency (2018). *Market report series: Energy efficiency*, 2018.

Jiang, L., Folmer, H., & Ji, M. (2014). The drivers of energy intensity in China: A spatial panel data approach. *China Economic Review*, *31*, 351–360.

Jiang, L., Folmer, H., Ji, M., & Zhou, P. (2018). Revisiting cross-province energy intensity convergence in China: A spatial panel analysis. *Energy Policy*, *121*, 252–263.

Jiang, X., Duan, Y., & Green, C. (2017). Regional disparity in energy intensity of China and the role of industrial and export structure. *Resources, Conservation and Recycling*, *120*, 209–218.

Kang, S., & Eltahir, E. A. (2018). North China Plain threatened by deadly heatwaves due to climate change and irrigation. *Nature Communications*, *9*(1), 1–9.

Kivimaa, P., & Kern, F. (2016). Creative destruction or mere niche support? Innovation policy mixes for sustainability transitions. *Research Policy*, *45*(1), 205–217.

Langel, M., & Tillé, Y. (2012). Inference by linearization for Zenga's new inequality index: A comparison with the Gini index. *Metrika*, *75*(8), 1093–1110.

Li, Y., Sun, L., Feng, T., & Zhu, C. (2013). How to reduce energy intensity in China: A regional comparison perspective. *Energy Policy*, *61*, 513–522.

Ma, B. (2015). Does urbanization affect energy intensities across provinces in China? Long-run elasticities estimation using dynamic panels with heterogeneous slopes. *Energy Economics*, *49*, 390–401.

Ma, L., Li, Z., Fu, F., Zhang, X., & Ni, W. (2009). Alternative energy development strategies for China towards 2030. *Frontiers of Energy and Power Engineering in China*, *3*(1), 2–10.

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.

Motiram, S., & Sarma, N. (2014). Polarization, inequality, and growth: The Indian experience. *Oxford Development Studies*, *42*(3), 297–318.

Organisation for Economic Co-operation and Development. (2012). OECD environmental outlook to 2050: The consequences of inaction.

Ou, J., Meng, J., Shan, Y., Zheng, H., Mi, Z., & Guan, D. (2019). Initial declines in China's provincial energy consumption and their drivers. *Joule*, *3*(5), 1163–1168.

Pasquazzi, L., & Zenga, M. (2018). Components of Gini, Bonferroni, and Zenga inequality indexes for EU income data. *Journal of Official Statistics*, *34*(1), 149–180.

Proskuryakova, L., & Kovalev, A. (2015). Measuring energy efficiency: Is energy intensity a good evidence base? *Applied Energy*, *138*, 450–459.

Qi, Y., Wu, T., He, J., & King, D. A. (2013). China's carbon conundrum. *Nature Geoscience*, *6*(7), 507–509.

Radaelli, P. (2010). On the decomposition by subgroups of the Gini index and Zenga's uniformity and inequality indexes. *International Statistical Review*, *78*(1), 81–101.

Ringius, L., Torvanger, A., & Holtsmark, B. (1998). Can multi-criteria rules fairly distribute climate burdens? OECD results from three burden sharing rules. *Energy Policy*, *26*(10), 777–793.

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.

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*, 170201.

Shan, Y., Huang, Q., Guan, D., & Hubacek, K. (2020). China CO_2 emission accounts 2016–2017. *Scientific Data*, *7*, 54.

Shan, Y., Zheng, H., Guan, D., Li, C., Mi, Z., Meng, J., et al. (2017). Energy consumption and CO_2 emissions in Tibet and its cities in 2014. *Earths Future*, *5*(8), 854–864.

Sun, X., Li, J., Qiao, H., & Zhang, B. (2017). Energy implications of China's regional development: new insights from multi-regional input-output analysis. *Applied Energy*, *196*, 118–131.

Tao, S., Ru, M. Y., Du, W., Zhu, X., Zhong, Q. R., Li, B. G., et al. (2018). Quantifying the rural residential energy transition in China from 1992 to 2012 through a representative national survey. *Nature Energy*, *3*(7), 567–573.

Voigt, S., De Cian, E., Schymura, M., & Verdolini, E. (2014). Energy intensity developments in 40 major economies: Structural change or technology improvement? *Energy Economics*, *41*, 47–62.

Wang, C., Guo, Y., Shao, S., Fan, M., & Chen, S. (2020). Regional carbon imbalance within China: An application of the Kaya-Zenga index. *Journal of Environmental Management*, *262*, 110378.

Wang, H., Zhang, Y., Zhao, H., Lu, X., Zhang, Y., Zhu, W., et al. (2017). Trade-driven relocation of air pollution and health impacts in China. *Nature Communications*, *8*(1), 1–7.

Wang, H., & Zhou, P. (2018). Assessing global CO_2 emission inequality from consumption perspective: An index decomposition analysis. *Ecological Economics*, *154*, 257–271.

Wu, Y. (2012). Energy intensity and its determinants in China's regional economies. *Energy Policy*, *41*, 703–711.

Xue, T., Zhu, T., Zheng, Y., & Zhang, Q. (2019). Declines in mental health associated with air pollution and temperature variability in China. *Nature Communications*, *10*(1), 1–8.

Yi, W. J., Zou, L. L., Guo, J., Wang, K., & Wei, Y. M. (2011). How can China reach its CO_2 intensity reduction targets by 2020? A regional allocation based on equity and development. *Energy Policy*, *39*(5), 2407–2415.

Zenga, M. (2007). Inequality curve and inequality index based on the ratios between lower and upper arithmetic means. *Statistica & Applizioni*, *5*, 3–27.

Zhang, B., Qiao, H., Chen, Z. M., & Chen, B. (2016). Growth in embodied energy transfers via China's domestic trade: Evidence from multi-regional input-output analysis. *Applied Energy*, *184*, 1093–1105.

Zhang, L., Yang, Z., Liang, J., & Cai, Y. (2011). Spatial variation and distribution of urban energy consumptions from cities in China. *Energies*, *4*(1), 26–38.

Zhang, N., & Zhou, M. (2020). The inequality of city-level energy efficiency for China. *Journal of Environmental Management*, *255*, 109,843.

Zhang, X., & Kanbur, R. (2001). What difference do polarisation measures make? An application to China. *Journal of Development Studies*, *37*(3), 85–98.

Zhang, X., Zhao, X., Jiang, Z., & Shao, S. (2017). How to achieve the 2030 CO_2 emission-reduction targets for China's industrial sector: Retrospective decomposition and prospective trajectories. *Global Environmental Change*, *44*, 83–97.