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Upgrading or downgrading: China's regional carbon emission intensity evolution and its determinants

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ABSTRACT

One of China's major national targets is to environmentally upgrade its economy. In this paper, we define environmental upgrading as lowering the carbon intensity. The disparities among China's regions suggest to examine China's carbon emission performance at the regional level. For this purpose, we use inter-regional input-output tables (for 2002, 2007, and 2012) that distinguish processing exports from ordinary exports. The regional emission intensities (EIs) show environmental downgrading in the period 2002–2007 and upgrading during 2007–2012. To identify the determinants of the evolution of regional EIs, we have employed a multiplicative structural decomposition analysis. Changes in direct emission coefficients and changes in production technology are found to be the major determinants. However, next to these standard determinants, we also evaluate the effects on the changes in regional EIs of changes in inter-regional trade and changes in inter-regional spillovers. Changing inter-regional trade is found to have increased the EI significantly in western and central regions. This suggests that more “dirty” production was shifted from coastal to inland regions. Our study yields clear policy recommendations for achieving China's transformation to a low-carbon economy.

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1. Introduction

Global warming has become one of the greatest environmental challenges that humans currently face. There is consensus among the world's scientists that this is mainly caused by the increase of carbon emissions emitted by anthropogenic activities (Moser, 2010). As the largest developing country and the “world's factory”, China became the world's leading emitter of carbon dioxide (CO₂) around 2006. In 2013, its emissions accounted for nearly 30% of the world's total CO₂ emissions from fossil fuels combustion (Quéré et al., 2015). As a response, China took its responsibility to mitigate CO₂ emissions. At the Paris Climate Change Conference in 2015, China committed itself to (i) have the peak of carbon emissions around 2030 (or earlier), and (ii) lower the carbon emission intensity (CO₂ emissions per unit of GDP) of its economy by 60% to 65% from the 2005 level.¹ The emission intensity (EI) captures the environmental costs (measured by CO₂ emissions in this paper) for a country to obtain economic gains (measured by

value-added) from production. An increase (decrease) in EI suggests that the country bears more (less) environmental costs for the same economic gains. Here, we call the increase (decrease) in EI environmental downgrading (upgrading).

Two specific aspects have motivated this paper. First, the top-down policy process. Commitments are in China made by the central government whilst local (regional) governments are the direct executive bodies in charge of the emission reductions. At the same time, however, local governments are pushed by the central government to improve economic performance, which normally has priority over the emission reduction target. Both forces influence EI, but in opposite ways. Second, China is a very large country with striking regional disparities in resource endowments, production technology, energy efficiency, industrial structures, and economic development level. As a result, the EIs and their evolution over time differ across regions. For example, the EIs of Ningxia and Shanxi, which are located in the Northwestern regions, were 12 and 8 times of that in Beijing, respectively (Wang et al., 2020). According to our estimation in Section 4, the EI of the Beijing-Tianjin region decreased by 37% from 2002 to 2012, but the EI of the Northwest increased by 27% in that period.

These two aspects suggest that China needs to strengthen the regional coordination of EI reduction in order to achieve its national targets for low-carbon transformation. It is therefore important that the evaluation of the development of EIs and the quantification of the

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¹These are China's intended nationally determined contributions (INDCs). Before that, China committed at the 2009 Copenhagen Climate Change Conference to reduce CO₂ emissions per unit of GDP by 40–45% towards 2020.

determinants (or drivers) of the changes in EIs take place at the regional level. This may help to check the effectiveness of environmental policies and to design more effective decarbonizing measures.

In this paper, we examine China's EIs at the regional level. We first check whether regional environmental upgrading has taken place, whether EIs differ much across regions, and whether the development of regional EIs over time is similar across regions. Subsequently, we employ a multiplicative Structural Decomposition Analysis (SDA) to identify what has driven the changes in regional EIs over the period 2002–2012 and to quantify how much each driver has contributed. In the analysis, we will define EI from the demand perspective. That is, both at the national and the regional level, we consider embodied EI indicators for domestic final demands and for international exports (Su and Ang, 2017). In particular, when studying the embodied EIs in exports, we distinguish between processing exports and ordinary exports.² This is important because processing exports account for a large share of China's export and because the production of processing exports differs largely from the production of ordinary exports (Chen et al., 2012; Koopman et al., 2012; Dietzenbacher et al., 2012; Su and Thomson, 2016). We will employ the (IRIOP) tables constructed by Duan et al. (2014) and Yan et al. (2020) for the years 2002, 2007, and 2012. These are inter-regional input-output (IRIO) tables that split the Chinese economy into 8 regions, each with 2 production types (production of processing exports and ordinary production) and 17 industry groups (see Appendix A for the region and sector classifications).

This paper contributes to the literature in two ways. First, we introduce new drivers in our multiplicative SDA. Standard drivers are changes in direct emission coefficients (emissions per unit of output), changes in the intermediate input structure, and changes in the final demands. Next to these standard drivers, we also include changes in inter-regional trade and changes in inter-regional spillovers as drivers of the changes in regional EIs.

The motivation to include these new drivers is as follows. Producers in a region can upgrade the region's emission performance in two different ways. First, by reducing their own emissions content and/or increasing the value-added content (both contents per unit of output). Second, by giving up the production of certain "dirty" products at home. Instead, the production is transferred to other regions after which the "dirty" products are imported. This results in inter-regional spillovers of carbon emissions. This second way follows the idea underlying the pollution haven hypothesis, albeit at a regional level. Given that China is a vast country with remarkable regional disparities and given that environmental pressures are exercised at the regional level, pollution havens are very likely to exist in China. As a response, the Chinese government released in 2010 a regulation called "Opinions of the State Council on the Transfer of Industries to the Central and Western Regions". This report targets the undesirable emission leakages (where the Central and Western regions emit for the regions on the East Coast). To the best of our knowledge, however, no study has considered the effect of emission leakages on China's regional EI evolution (see the next section for a review of the literature). We analyze how and to what extent changes in inter-regional trade and in inter-regional spillovers changed China's regional EIs.

The second contribution of this paper to the literature is that it combines two research lines that have been separate hitherto. One line of research deals with China's regional emissions and the other line deals with China's processing exports. Previous studies on China's regional emissions have largely neglected the role of processing exports. Vice versa, most studies on processing exports were only at the national level. Although the share of processing exports in total exports declined

from 55.3% in 2002 to 33.7% in 2019, it still is very substantial.³ An important feature of China's processing exports is its uneven distribution over the regions, with the main concentration in coastal regions. For example, in 2012, over half of South Coast exports can be attributed to processing exports, while in the Northwest region the share is less than 10%. Over time, the share of processing exports has been decreasing for most regions, but not for every region. Some previous work (e.g. Dietzenbacher et al., 2012; Su et al., 2013; Yan et al., 2020) suggests that production for processing exports is relatively clean. Therefore, when studying China's export-related emissions it is important to distinguish between production for processing exports and other production. However, to our knowledge, few studies have quantified whether and to what extent a region's changes in processing exports contribute to the changes in its EI.

The rest of this paper is organized as follows. After briefly reviewing the current studies on China's regional emissions in Section 2, we introduce the details of our analytic approach and discuss the data in Section 3. Section 4 describes the evolution of China's regional emissions and Section 5 presents and analyzes the decomposition results. Finally, Section 6 offers conclusions and policy implications.

2. Literature review

Carbon emission intensity is a globally adopted indicator by policymakers and researchers to evaluate emission performance. In response to the problem of global warming, a number of countries (e.g., China, South Korea, and India) have set reduction targets in terms of EI (UNFCCC, 2015). Several studies have analyzed EIs from a regional, national and global perspective (e.g., Zhang et al., 2014; Su and Ang, 2015; Ang and Su, 2016; Su and Ang, 2017; Duan and Yan, 2019; Wang et al., 2020), and decomposition analysis has been widely used to analyze the determinants of changes in EIs. Two most frequently used decomposition methods are Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA). IDA uses aggregate sector information and captures direct effects mainly from a production-based perspective, and IDA can handle both quantity and intensity indicators (see, e.g. Ang, 2004 for a review of IDA). Applications of IDA to the decomposition of changes in EI include Fan et al. (2007) and Chen (2011). In contrast, SDA (which is typically based on an input-output model) is able to capture explicitly both production-side and demand-side effects (Miller and Blair, 2009). SDA studies use either an additive decomposition (see Su and Ang, 2012 for a survey of SDA studies using additive decompositions) or a multiplicative decomposition, depending on the purposes. In this paper, we aim at identifying the drivers of changes in China's regional EI between 2002 and 2012. Because EI is determined as a ratio, we adopt a multiplicative SDA framework.

Because China is the largest emitter of global carbon emissions, a growing list of SDA studies analyzes China's emission intensity evolution. The first strand of literature covers analyses at the national level. For example, Su and Ang (2015) introduced four different models to calculate a country's aggregate EI using the input-output framework. Using the four models and multiplicative SDA, they investigated the determinants of the change in China's aggregate EI from 2007 to 2010. Later, Su and Ang (2017) showed that the aggregate EI can be expressed as a weighted summation of the EIs for final demand categories or for

² Processing exports follow from the business activity of importing from abroad all, or part of, the raw and auxiliary materials, parts and components, accessories, and packaging materials, and re-exporting the finished products after processing or assembly by enterprises in China. In this paper, the processing exports include both the exports of processing with imported materials and the exports of processing and assembly.

³ The data are from China's National Bureau of Statistics. The reasons for this decline are twofold. On the one hand, a change in trade policy. Triggered by a very biased policy, China had a large share of processing exports in its total exports around the 2000s. After decades of rapid trade growth, the policy regarding processing trade changed in the mid-2000s. In 2006, the Ministry of Commerce selected several commodities for which processing trade became prohibited or restricted. In 2015, processing exports were prohibited for 1862 commodities, accounting for 14% of all commodities at ten-digit Harmonized System codes (Announcement No.59 of 2015 of the Ministry of Commerce, PRC). On the other hand, a change in wage policy. China's reform in 2004 of its minimum-wage policy effectively increased labor costs in China (and cheap labor was one of the major reasons to carry out processing and assembly activities in China).

sectors. They further employed multiplicative SDA to analyze China's aggregate EI reduction during 2007–2012. More recently, Yan et al. (2018) applied multiplicative SDA to both the Leontief and the Ghosh model to investigate China's EI changes during 2002–2012. Su et al. (2019) combined structural path analysis with SDA to extract the important paths and driving forces of EI reduction.

The second strand of literature covers analyses of China's EI at the sub-national (i.e. regional and provincial) level. This was made possible by the improvement of China's regional statistics on environmental aspects. For example, Su and Ang (2016) compared the emission performance across 30 regions in China and employed spatial-SDA to explain the EI differences between pairs of regions. Whereas a number of studies analyzed China's emissions at the regional level (e.g., Meng et al., 2013, 2017; Li et al., 2017), only Wang et al. (2020) focused on regional EI evolution. They extended the methods of Su and Ang (2017) to a provincial setting and adopted multiplicative SDA to quantify the contribution of the drivers to the EI changes in the period 2007–2012 for China's 30 provincial units. Next to the standard drivers that were also included in Wang et al. (2020), this paper also includes other drivers (changes in inter-regional trade and in inter-regional spillovers). These additional drivers follow from extending Oosterhaven and Hoen (1998) and Xu and Dietzenbacher (2014) to an inter-regional framework. Given that China is a vast country with large regional disparities, carbon leakages between regions are present (Meng et al., 2017; Wen and Wang, 2020). Therefore, it is important to investigate how changes in inter-regional trade effect and in inter-regional spillovers contribute to changes in regional EIs.

This paper is also closely related to studies that focus on China's EI embodied in international trade. This EI embodied in trade is defined as the ratio of emissions embodied in trade to value-added embodied in trade. Using global multi-region input-output (GMRIO) tables, Wang et al. (2017) proposed two SDA models and quantified both the domestic and trade related effects on global and countries' emission intensities from 2000 to 2009. Also Duan and Yan (2019) conducted an SDA of the pollution intensity of China's value-added exports.

The aforementioned studies that were undertaken at the regional level neglected the production of processing exports. Processing trade has primarily been studied at the national level. Chen et al. (2012), Koopman et al. (2012), and Su et al. (2013) have differentiated processing exports from other production in China's national input-output tables. They consistently concluded that processing exports rely heavily on imported intermediates. When compared to other production, producing processing exports generates less domestic activities and therefore less domestic value added. Failing to distinguish processing exports biases the intermediate input structure which may seriously affect the outcomes, e.g. on export-related emission. Examples include Dietzenbacher et al. (2012) and Su and Thomson (2016), who documented that the damage of international trade to China's environment would be significantly overestimated if processing exports were not distinguished. More recently, Chen et al. (2019) proposed an adapted GMRIO model which splits China's national production into production for domestic use, production of processing exports, and production of non-processing exports. Jiang et al. (2016) revisited the global net emission transfers by applying such an adapted GMRIO table and found that the results obtained with traditional tables overestimated the net emissions from China to other countries by 15%. All the results in previous studies suggest that processing exports are relatively cleaner than ordinary exports in the sense that they have a lower embodied EI. This emphasizes the necessity to separate processing exports from ordinary exports.

At the regional level, to the best of our knowledge, only a few studies (Jiang et al., 2017; Zhang et al., 2019; Yan et al., 2020) recently distinguished processing exports in China's IRIO table. Jiang et al. (2017) employed an IRIO table that separates processing exports to study China's regional disparity of energy intensity. However, their data do not cover emissions and are only for 2007. Also Zhang et al. (2019) took processing exports into account and focused on investigating the unbalanced distribution of trade-related economic benefits and environmental costs across different regions

Table 1
The inter-regional input-output table distinguishing processing exports (IRIOP table).

	Intermediate use					Domestic			EXP	TOT	
	in 1		... in n			final use					
	P	O	...	P	O	1	...	n			
Region 1	P	0	0	...	0	0	0	...	0	e_1^P	y_1^P
	0	Z_{11}^{OP}	Z_{11}^{OO}	...	Z_{1n}^{OP}	Z_{1n}^{OO}	f_{11}^O	...	f_{1n}^O	e_1^O	y_1^O
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Region n	P	0	0	...	0	0	0	...	0	e_n^P	y_n^P
	0	Z_{n1}^{OP}	Z_{n1}^{OO}	...	Z_{nn}^{OP}	Z_{nn}^{OO}	f_{n1}^O	...	f_{nn}^O	e_n^O	y_n^O
IMP		Z_1^{MP}	Z_1^{MO}	...	Z_n^{MP}	Z_n^{MO}	f_1^M	...	f_n^M	0	y^M
VA		$(w_1^P)'$	$(w_1^O)'$...	$(w_n^P)'$	$(w_n^O)'$					
TOT		$(y_1^P)'$	$(y_1^O)'$...	$(y_n^P)'$	$(y_n^O)'$					
Emissions		$(\rho_1^P)'$	$(\rho_1^O)'$...	$(\rho_n^P)'$	$(\rho_n^O)'$					

Notes: P = production of processing exports; O = ordinary production, containing production of non-processing exports and production for domestic use; Domestic final use = household consumption, government expenditures, gross fixed capital formation, and changes in inventories; EXP = exports; TOT = gross sector outputs or total imports; IMP = imports; VA = value added.

in 2007 and 2012. Yan et al. (2020) used the new IRIOP tables to reestimate the emissions embodied in regional exports. No study so far has analyzed (the evolution of) China's regional EIs with IRIOP tables. We aim to fill this gap by applying SDA to the IRIOP tables.

3. Methodology and data

3.1. An inter-regional input-output table distinguishing processing exports

Our starting point is a unique inter-regional input-output table proposed by Duan et al. (2014), which distinguishes between the input structures of production of processing exports and ordinary production (IRIOP table). The general structure of the IRIOP table is outlined in Table 1. The unique feature of the IRIOP table is that domestic production of each region and each industry is divided into two types: production for processing exports and ordinary production.

China⁴ is grouped into n regions with g sectors (or industries) in each region. In the IRIOP table, two types of production are distinguished for each industry: production of processing exports (indicated by superscript P), and ordinary production (indicated by superscript O). Ordinary production contains production of non-processing exports and production for domestic use. Aggregation over the production types within each region in the IRIOP table yields the ordinary IRIO table. The $g \times g$ matrix Z_{sr}^{OP} (or Z_{sr}^{OO}) denotes the sector-wise intermediate inputs produced by ordinary production in region s and used in region r for processing exports (or ordinary production). Note that processing exports are exclusively used for foreign demand, and therefore the (row) sales of processing exports (P) are zero in intermediate use and domestic final use. The value of goods and services shipped from region s to region r for domestic final use (domestic household consumption, government expenditures, gross fixed capital formation, and inventory changes) is given by the $g \times 1$ vector f_{sr}^O . The $g \times 1$ vector e_s^P (or e_s^O) gives the sector-wise processing exports (or non-processing exports) of region s . The vector y_s^P (or y_s^O) represents the domestic gross output for processing exports (or ordinary production) of region s . The accounting identity (or product market clearing condition) is

$$\begin{pmatrix} y_1^P \\ y_1^O \\ \vdots \\ y_n^P \\ y_n^O \end{pmatrix} = \begin{bmatrix} 0 & 0 & \dots & 0 & 0 \\ Z_{11}^{OP} & Z_{11}^{OO} & \dots & Z_{1n}^{OP} & Z_{1n}^{OO} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 \\ Z_{n1}^{OP} & Z_{n1}^{OO} & \dots & Z_{nn}^{OP} & Z_{nn}^{OO} \end{bmatrix} \begin{pmatrix} u \\ u \\ \vdots \\ u \\ u \end{pmatrix} + \begin{pmatrix} 0 \\ \sum_t f_{1t}^O \\ \vdots \\ 0 \\ \sum_t f_{nt}^O \end{pmatrix} + \begin{pmatrix} e_1^P \\ e_1^O \\ \vdots \\ e_n^P \\ e_n^O \end{pmatrix} \quad (1)$$

⁴ In this paper, China does not include Taiwan and (because of data unavailability) the special administrative regions of Hong Kong and Macao.

where \mathbf{u} indicates the summation vector of appropriate length consisting entirely of ones.

Define the domestic input coefficient matrix $\mathbf{A}_{sr}^{OP} = \mathbf{Z}_{sr}^{OP}(\hat{\mathbf{y}}_r^P)^{-1}$ (or $\mathbf{A}_{sr}^{OO} = \mathbf{Z}_{sr}^{OO}(\hat{\mathbf{y}}_r^O)^{-1}$), which denotes the sector-wise intermediate inputs from ordinary production in region s and used in region r for producing one unit of output of processing exports (or ordinary production). This yields

$$\begin{pmatrix} \mathbf{y}_1^P \\ \mathbf{y}_1^O \\ \vdots \\ \mathbf{y}_n^P \\ \mathbf{y}_n^O \end{pmatrix} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{A}_{11}^{OP} & \mathbf{A}_{11}^{OO} & \cdots & \mathbf{A}_{1n}^{OP} & \mathbf{A}_{1n}^{OO} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{A}_{n1}^{OP} & \mathbf{A}_{n1}^{OO} & \cdots & \mathbf{A}_{nn}^{OP} & \mathbf{A}_{nn}^{OO} \end{bmatrix} \begin{pmatrix} \mathbf{y}_1^P \\ \mathbf{y}_1^O \\ \vdots \\ \mathbf{y}_n^P \\ \mathbf{y}_n^O \end{pmatrix} + \begin{pmatrix} \mathbf{0} \\ \sum_t \mathbf{f}_{1t}^O \\ \vdots \\ \mathbf{0} \\ \sum_t \mathbf{f}_{nt}^O \end{pmatrix} + \begin{pmatrix} \mathbf{e}_1^P \\ \mathbf{e}_1^O \\ \vdots \\ \mathbf{e}_n^P \\ \mathbf{e}_n^O \end{pmatrix} \quad (2)$$

In compact form, this system can be rewritten as $\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{f} + \mathbf{e}$ and the solution is given by

$$\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}(\mathbf{f} + \mathbf{e}) = \mathbf{L}(\mathbf{f} + \mathbf{e}) \quad (3)$$

where \mathbf{I} is the $2ng \times 2ng$ identity matrix, and $\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse. In its partitioned, this matrix is given by

$$\mathbf{L} = \begin{bmatrix} \mathbf{I} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{L}_{11}^{OP} & \mathbf{L}_{11}^{OO} & \cdots & \mathbf{L}_{1n}^{OP} & \mathbf{L}_{1n}^{OO} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I} & \mathbf{0} \\ \mathbf{L}_{n1}^{OP} & \mathbf{L}_{n1}^{OO} & \cdots & \mathbf{L}_{nn}^{OP} & \mathbf{L}_{nn}^{OO} \end{bmatrix}$$

Define λ' as the $1 \times 2ng$ row vector of carbon emissions coefficient representing the sector-wise carbon emissions per unit of output by production type and region, with $(\lambda_s^P)' = (\rho_s^P)'(\hat{\mathbf{y}}_s^P)^{-1}$ and $(\lambda_s^O)' = (\rho_s^O)'(\hat{\mathbf{y}}_s^O)^{-1}$. Then carbon emissions generated by domestic final use and exports via domestic inter-regional and inter-industrial supply chains are given by $\mathbf{p} = \hat{\mathbf{L}}\mathbf{L}(\mathbf{f} + \mathbf{e})$, where a hat symbol indicates a diagonal matrix with the element of a vector on the diagonal. For a specific region s , its carbon emissions can be decomposed as follows:

$$\mathbf{c}_s = \rho_s^P + \rho_s^O = \hat{\lambda}_s^O \sum_k \mathbf{L}_{sk}^{OO} (\sum_t \mathbf{f}_{kt}^O) + \hat{\lambda}_s^P \mathbf{e}_s^P + \hat{\lambda}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P + \hat{\lambda}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O \quad (4)$$

where \mathbf{c}_s is the $g \times 1$ vector gives sector-wise emissions generated in the g industries. This equation reflects the fact that a region's emissions (\mathbf{c}_s) depend on its own carbon emissions coefficient, its own and other regions' final demands, and exports (including both processing and non-processing exports) via domestic supply chains. The first term in eq. (4) is emissions generated by domestic final demands. The second is emissions generated in production type P to produce the own processing exports and the third term gives the emissions generated in region s when producing the inputs of type O necessary for all the processing exports. The last term is emissions generated by non-processing exports. The aggregate emissions in region s for domestic final demand and exports is given by $c_s = \mathbf{u}' \mathbf{c}_s$.

In the same way as we measured carbon emissions, we can also measure value-added generated by domestic final demand and exports in the same way. Let \mathbf{v}' be the $1 \times 2ng$ vector of value-added coefficient representing sector-wise value-added per unit of output, with $(\mathbf{v}_s^P)' = (\mathbf{w}_s^P)'(\hat{\mathbf{y}}_s^P)^{-1}$ and $(\mathbf{v}_s^O)' = (\mathbf{w}_s^O)'(\hat{\mathbf{y}}_s^O)^{-1}$. Then value-added generated by domestic final demand and exports is given by $\mathbf{w} = \hat{\mathbf{L}}\mathbf{L}(\mathbf{f} + \mathbf{e})$. Similar to eq. (4), the value-added generated in region s can be decomposed as follows:

$$\mathbf{v}_s = \mathbf{w}_s^P + \mathbf{w}_s^O = \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OO} (\sum_t \mathbf{f}_{kt}^O) + \hat{\mathbf{v}}_s^P \mathbf{e}_s^P + \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P + \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O \quad (5)$$

Aggregate value-added in region s is given by $va_s = \mathbf{u}' \mathbf{v}_s$. The aggregate emission intensity (El) of production in region s is given by:

$$El_s = c_s/va_s = \mathbf{u}' \mathbf{c}_s / \mathbf{u}' \mathbf{v}_s \quad (6)$$

The emission intensity measures the emissions a region generates in order to obtain one unit of value-added. The numerator proxies the environmental costs in region s from its production and the denominator proxies the economic gains from its production. A larger emission intensity suggests that the region has higher environmental costs for each unit of economic gain.

In the empirical analysis, we will also analyze the regional EI for separate final demand categories (domestic consumption, investment, and international exports). It is possible to measure the EI of region s for a specific final demand category with a slight adaptation of Eqs. (4) and (5). For example, for the EI of processing exports one only keeps the demand for processing exports in Eqs. (4) and (5) instead of accounting for all final demand categories. In particular, we will compare the regional EIs of all exports (i.e. El_s^e) using the IRIOP tables and using the traditional IRIO tables without distinguishing processing exports.⁵ Denote El_s^{pe} and El_s^{oe} as the emission intensity of processing exports and ordinary exports, respectively.⁶ Then the weighted summation of El_s^{pe} and El_s^{oe} yields the aggregate emission intensity of exports (El_s^e). That is,

$$\omega_s^{pe} \cdot El_s^{pe} + \omega_s^{oe} \cdot El_s^{oe} = El_s^e \quad (7)$$

where ω_s^{pe} denotes the value added embodied in processing exports as a share of the value added embodied in all exports (both processing and ordinary exports) and ω_s^{oe} is the share of the embodied value added by ordinary exports. Note that $\omega_s^{pe} + \omega_s^{oe} = 1$. This idea is similar to that presented by Su and Ang (2017).

3.2. Multiplicative structural decomposition analysis

It is clear that the value of El_s in Eq. (6) depends on: the emission coefficients vector λ_s , with $(\lambda_s)' = ((\lambda_s^O)' (\lambda_s^P)')$; the value-added coefficients vector \mathbf{v}_s , with $(\mathbf{v}_s)' = ((\mathbf{v}_s^O)' (\mathbf{v}_s^P)')$; the domestic final demands vector $\sum_t \mathbf{f}_{st}^O$; the two exports vectors \mathbf{e}_k^P and \mathbf{e}_k^O ; and the Leontief inverse \mathbf{L} , which in its turn relies on the input matrix \mathbf{A} . Our SDA is based on Arto and Dietzenbacher (2014) and Xu and Dietzenbacher (2014). We follow Oosterhaven and Hoen (1998) in splitting the inter-regional domestic intermediate inputs matrix \mathbf{A} . We split \mathbf{A} into three parts. (a) A part that gives the overall production technology (\mathbf{T}), reflecting the total intermediate inputs that are required per unit of output, (b) a part that gives the domestic shares (\mathbf{S}), reflecting the substitution effect between domestic and imported intermediate inputs, and (c) a part that gives the regional shares (Φ), which captures the structure of inter-regional trade in intermediate inputs. Define the $2ng \times 2ng$ matrices \mathbf{T} , \mathbf{S} and Φ as.

⁵ The calculation of the EI of exports based on the traditional IRIO tables follows the same methodology, except for the distinction between P and O . More details about the comparison between IRIOP model and the traditional IRIO model are given in Yan et al. (2020).

⁶ $El_s^{pe} = \mathbf{u}' (\hat{\lambda}_s^P \mathbf{e}_s^P + \hat{\lambda}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P) / \mathbf{u}' (\hat{\mathbf{v}}_s^P \mathbf{e}_s^P + \hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OP} \mathbf{e}_k^P)$ and $El_s^{oe} = \mathbf{u}' (\hat{\lambda}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O) / \mathbf{u}' (\hat{\mathbf{v}}_s^O \sum_k \mathbf{L}_{sk}^{OO} \mathbf{e}_k^O)$.

$$\begin{aligned}
 \mathbf{T} &= \begin{bmatrix} \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{T}_1^{OP} & \mathbf{T}_1^{OO} & \dots & \mathbf{T}_n^{OP} & \mathbf{T}_n^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{T}_1^{OP} & \mathbf{T}_1^{OO} & \dots & \mathbf{T}_n^{OP} & \mathbf{T}_n^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{S}_1^{OP} & \mathbf{S}_1^{OO} & \dots & \mathbf{S}_n^{OP} & \mathbf{S}_n^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{S}_1^{OP} & \mathbf{S}_1^{OO} & \dots & \mathbf{S}_n^{OP} & \mathbf{S}_n^{OO} \end{bmatrix}, \text{ and} \\
 \mathbf{S} &= \begin{bmatrix} \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{S}_1^{OP} & \mathbf{S}_1^{OO} & \dots & \mathbf{S}_n^{OP} & \mathbf{S}_n^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{S}_1^{OP} & \mathbf{S}_1^{OO} & \dots & \mathbf{S}_n^{OP} & \mathbf{S}_n^{OO} \end{bmatrix}, \text{ and} \\
 \Phi &= \begin{bmatrix} \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \Phi_{11}^{OP} & \Phi_{11}^{OO} & \dots & \Phi_{1n}^{OP} & \Phi_{1n}^{OO} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \Phi_{n1}^{OP} & \Phi_{n1}^{OO} & \dots & \Phi_{nn}^{OP} & \Phi_{nn}^{OO} \end{bmatrix},
 \end{aligned}$$

with the $g \times g$ sub-matrices $\mathbf{T}_r^{OP} = \sum_{k=1}^n \mathbf{A}_{kr}^{OP} + \mathbf{M}_r^P$ and $\mathbf{T}_r^{OO} = \sum_{k=1}^n \mathbf{A}_{kr}^{OO} + \mathbf{M}_r^O$ ($r = 1, \dots, n$). These technology matrices give the total amount of inputs per unit of output irrespective of their geographical source. Here \mathbf{M}_r^P and \mathbf{M}_r^O are matrices with imported input coefficients, which are derived as $\mathbf{M}_r^P = \mathbf{Z}_r^{MP}(\hat{\mathbf{y}}_r^P)^{-1}$ and $\mathbf{M}_r^O = \mathbf{Z}_r^{MO}(\hat{\mathbf{y}}_r^O)^{-1}$. The matrices with domestic shares are given by $\mathbf{S}_r^{OP} = (\sum_{k=1}^n \mathbf{A}_{kr}^{OP}) / \mathbf{T}_r^{OP}$ and $\mathbf{S}_r^{OO} = (\sum_{k=1}^n \mathbf{A}_{kr}^{OO}) / \mathbf{T}_r^{OO}$. They express the shares of all required inputs that are sourced domestically. Here // denotes element-wise division. The matrices with regional shares are given by $\Phi_{kr}^{OP} = \mathbf{A}_{kr}^{OP} / (\sum_{k=1}^n \mathbf{A}_{kr}^{OP})$ and $\Phi_{kr}^{OO} = \mathbf{A}_{kr}^{OO} / (\sum_{k=1}^n \mathbf{A}_{kr}^{OO})$. This yields $\mathbf{A} = \mathbf{T} \otimes \Phi \otimes \mathbf{S}$, where the Hadamard product \otimes indicates cell-by-cell multiplication.

The emission intensity of region s can now be written as a function of seven matrices and vectors (please refer to Appendix B for the explicit expression). That is:

$$EI_s = f(\lambda_s, \mathbf{v}_s, \mathbf{T}, \Phi, \mathbf{S}, \mathbf{F}, \mathbf{e}) \tag{8}$$

To examine to what extent a region's emission intensity is affected by intra-regional factors and inter-regional spillover effects, we split \mathbf{T} , Φ and \mathbf{S} into two parts. That is, for region r , within the region ($\mathbf{T}_{(r)}$, $\Phi_{(r)}$ and $\mathbf{S}_{(r)}$) and outside the region ($\mathbf{T}_{(-r)}$, $\Phi_{(-r)}$ and $\mathbf{S}_{(-r)}$), where $\mathbf{T}_{(r)}$ includes the columns of \mathbf{T} that correspond to region r and all other columns are zero. We thus have $\mathbf{T} = \mathbf{T}_{(r)} + \mathbf{T}_{(-r)}$. By analogy, the other matrices and vectors can also be split into two parts depending on the research purpose.

The idea of an SDA is to consider the change in EI due to the change in one driver, assuming the other drivers remain unchanged. Dietzenbacher and Los (2000) explicated that this means that the drivers need to be independent, in the sense that –technically speaking– it must be possible to change one driver without having to change another driver. In the present case, this requirement is violated, because by definition we have $\mathbf{u}'\mathbf{T} + \mathbf{v}' = \mathbf{u}'$. It is thus not possible to change \mathbf{v} without changing \mathbf{T} . The solution that we use is to consider changes in \mathbf{v} and \mathbf{T} together. In our tables with results, we denote this combined effect as \mathbf{T}^* . This indicates the effects of changes in production technology, combining changes in inputs and values added (Su and Ang, 2017).

It has long been recognized in the literature on SDA that decompositions are not unique. To overcome this non-uniqueness problem, Dietzenbacher and Los (1998) have indicated that the average of all decompositions can be adequately approximated by the average of the two so-called polar decomposition forms. De Haan (2001) extended this result to the average of any two “mirror” decompositions. In this paper, we use the average of the two polar forms.

The first polar form is derived by starting the decomposition with changing the first variable first, followed by changing the second variable, changing the third variable, and so forth. The second polar form is derived exactly the other way around. That is, by changing the last

variable first, followed by changing the one but last variable, etcetera. The explicit expression of the two polar forms, is given in Appendix B. The final decomposition is obtained as the geometric average of the two polar forms.

As mentioned above, another aim of this paper is to analyze how changes in processing exports affect the EIs embodied in exports. Thus, we split the exports vector \mathbf{e} , and define.

$$\mathbf{e} = \begin{pmatrix} \mathbf{e}_1^P \\ \mathbf{e}_1^O \\ \vdots \\ \mathbf{e}_n^P \\ \mathbf{e}_n^O \end{pmatrix}, \mathbf{b} = \begin{pmatrix} \mathbf{b}^{Tot} \\ \mathbf{b}^{Tot} \\ \vdots \\ \mathbf{b}^{Tot} \\ \mathbf{b}^{Tot} \end{pmatrix}, \mathbf{h} = \begin{pmatrix} \mathbf{h}_1 \\ \mathbf{h}_1 \\ \vdots \\ \mathbf{h}_n \\ \mathbf{h}_n \end{pmatrix}, \text{ and } \mathbf{x} = \begin{pmatrix} \mathbf{x}_1^P \\ \mathbf{x}_1^O \\ \vdots \\ \mathbf{x}_n^P \\ \mathbf{x}_n^O \end{pmatrix}$$

with $\mathbf{b}^{Tot} = \sum_k^n (\mathbf{e}_k^P + \mathbf{e}_k^O)$, which gives the vector of total exports of each product, $\mathbf{h}_k = (\mathbf{e}_k^P + \mathbf{e}_k^O) / \mathbf{b}^{Tot}$, which gives the shares of exports (in total exports) by region k for each product, and $\mathbf{x}_k^P = \mathbf{e}_k^P / (\mathbf{e}_k^P + \mathbf{e}_k^O)$, which gives the shares of processing exports (in exports of region k), and $\mathbf{x}_k^O = \mathbf{e}_k^O / (\mathbf{e}_k^P + \mathbf{e}_k^O) = \mathbf{u} - \mathbf{x}_k^P$, which gives the shares of ordinary exports. We then have $= \mathbf{x} \otimes \mathbf{h} \otimes \mathbf{b}$. This implies that we can write the emission intensity embodied in exports in eq. (7) as $EI_s^e = f(\lambda_s, \mathbf{v}_s, \mathbf{L}, \mathbf{x}, \mathbf{h}, \mathbf{b})$. Subsequently, we employ multiplicative SDA to calculate the contributions of each driver.

3.3. Data

Implementing the decomposition analysis outlined above requires IRIOP tables and the corresponding CO₂ emissions data by region, by industry and by production type. The IRIOP tables for the years 2002, 2007 and 2012 were compiled by Duan et al. (2014). Their compilation of IRIOP tables was based on two types of IO tables. The first is the Chinese IRIOP table compiled by China State Information Center (SIC) and the National Bureau of Statistics of China (NBS) (Zhang and Qi, 2012). The second is the tripartite national IO table compiled by the Chinese Academy of Sciences (CAS) and the NBS (Chen et al., 2012). The unique table distinguishes between the production of processing exports, of ordinary exports and other production (which is largely domestic use).

Assuming proportionality and applying a bi-proportional estimation procedure (RAS), Duan et al. (2014) nested the IRIOP table within the national bipartite table and constructed the new IRIOP table.⁷ In the process, other provincial statistics were used to ensure the IRIOP table is balanced and consistent with the official statistics. These statistics include Chinese provincial economic accounts (for data on, for example, value added, final consumption, and fixed capital formation at the sectoral level), and provincial customs statistics by trade regime (i.e. processing trade and ordinary trade) and by commodity (at the 8-digit level under the Harmonized Commodity Description and Coding System). All data are provided by NBS. Following the regional and sector classifications used in Chinese IRIOP tables, China in the IRIOP table is divided into eight geographical regions: Northeast, Northern Municipalities, North Coast, East Coast, South Coast, Central region, Northwest, and Southwest. Each region distinguishes 17 industries.

The CO₂ emissions data by region, by industry and by production type is the other necessary dataset for our calculation. They were compiled by Yan et al. (2020), who conducted three steps to estimate the data. First, they estimated the province-industry-level energy use data by adapting statistics from the China Energy Statistical Yearbooks (CESY) and the Provincial Statistical Yearbooks (PSY), considering 17 types of fossil fuels. Second, they estimated the CO₂ emissions data for 43 industries in each province, following the estimation procedure in the Intergovernmental Panel on Climate Change guidelines (IPCC, 2006; Peters et al., 2006; and Guan et al., 2012). Third, combining the

⁷ The national bipartite table is aggregated from the national tripartite table, by taking production of ordinary exports and other production together. For a full exposition of the estimation procedure the IRIOP table, see Duan et al. (2014).

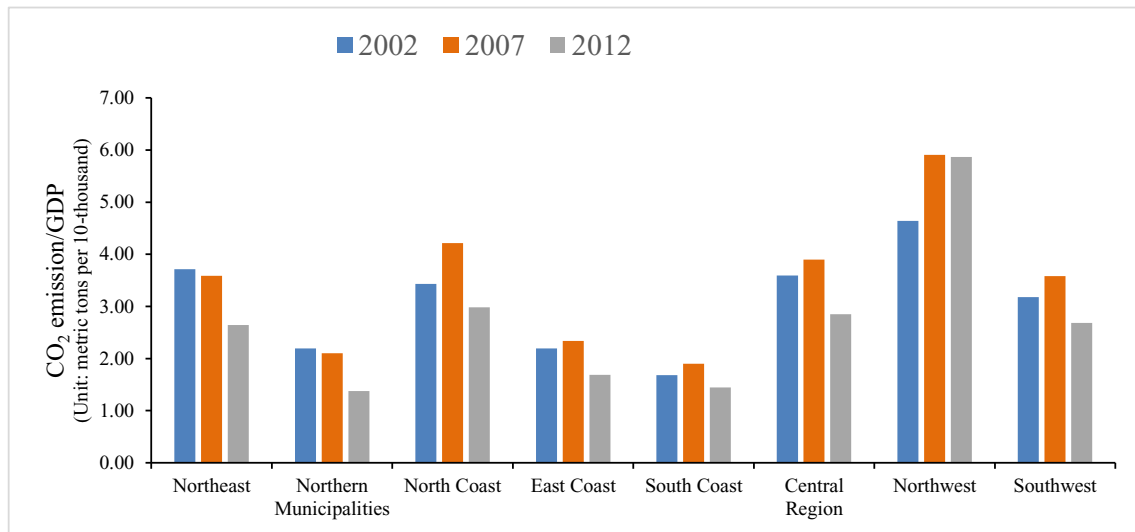


Fig. 1. Evolution of China's regional CO₂ emission intensity. Notes: To calculate regional emission intensity and make the figures in the three years comparable, we use provincial GDP deflator to adjust nominal GDP in 2007 and 2012 into that at constant 2002 price (base year: 2002).

method in [Dietzenbacher et al. \(2012\)](#) and [Jiang et al. \(2015\)](#), they split the region-industry-specific emissions into the emissions by different production types (processing production and ordinary production). The estimation was based on the extent to which each production type relies on domestic intermediate inputs. This is reasonable since less domestic intermediate inputs implies less activities and thus less emissions in the production processes. The production of processing exports relies heavily on imported inputs and requires primarily domestic labor for assembly. It is therefore expected to emit less emissions than ordinary production.

We are aware of one other database that provides disaggregated IRIO tables of China. For example, provincial level IRIO tables with 30 sectors are already available ([Liu et al., 2018](#)). Although spatially more detailed than the eight regions in [Yan et al. \(2020\)](#), the provincial IRIO tables do not distinguish processing exports. Failing to separate processing exports biases the intermediate input structure ([Chen et al., 2019](#)), which further biases the decomposition results.

4. China's regional CO₂ emission intensity evolution

We start in subsection 4.1 with the stylized facts of regional emission intensities. Subsection 4.2 deals with the EIs for separate final demand categories (domestic final demands and international exports).

4.1. China's CO₂ emission intensity by region

China's total CO₂ emissions increased from 3595 million metric tons (Mt) in 2002 to 9092 Mt. in 2012, observing a significant growth rate of 153%.⁸ [Fig. 1](#) gives the EIs across the eight regions.

The first observation is that there are large regional disparities in the EI levels. The levels of Northern Municipalities (Beijing-Tianjin region) and two of the coastal regions (South Coast and East Coast) are

⁸ The CO₂ emissions obtained in the present study is the same as those in [Yan et al. \(2020\)](#). They differ from those in earlier studies. For example, China's estimate of CO₂ emissions in 2007 in this paper is 7060 Mt., whilst they are 6386 Mt. in [Su and Ang \(2014\)](#) and 6081 Mt. in [Su and Ang \(2017\)](#). It should be noted that such differences may be caused by, for example, using different data sources, different aggregation of industries and regions. A major difference of estimating emissions in [Yan et al. \(2020\)](#) is that they adopt new emission factors from [Liu et al. \(2015\)](#) and [Shan et al. \(2018\)](#). These new emission factors are updated according to the survey on China's fossil fuel quality and the production process of cement. The new factors are more accurate than the historical default values from other reports (such as IPCC).

clearly smaller than those of inland regions. In other words, the production in coastal regions is relatively clean (i.e. less emissions for the same 'earnings'). [Fig. 2](#) shows that Northern Municipalities had the smallest EI (1.38 tons CO₂ per 10-thousand RMB of value-added generation) in 2012. It was closely followed by South Coast and East Coast (1.44 and 1.69 tons per 10-thousand RMB, respectively). In contrast, the EI in Northwest was 5.87 tons per 10-thousand RMB. Northwest had a high carbon-intensive industrial structure, with 37% of its outputs concentrated in high-carbon manufacturing products. Northern Municipalities and the two south-eastern coastal regions had a cleaner industrial structure and were becoming more service-oriented. In addition did these regions face more rigorous environmental regulations to which they often responded by improving production technology. The results for 2002 and 2007 sketch a similar picture. Thus, the regional pattern of EIs is one of large disparities that are stable over time.

The second observation is that the EIs at both the national and the regional level (except Northwest) decreased from 2002 to 2012, indicating that the carbon emission performance upgraded. That is, China and its sub-regions emitted in 2012 less CO₂ to generate the same value-added than in 2002. However, we also observe that the carbon emission performance downgraded during 2002–2007 (see [Guan et al., 2014](#) for similar results) but upgraded more during 2007–2012. This is because we see that most regions (except Northern Municipalities and Northeast) increased their EIs in the first period and all regions showed a decrease in the second period. The result for the period 2007–2012 is consistent with that obtained by [Su and Ang \(2017\)](#) and [Wang et al. \(2020\)](#). The efforts to upgrade carbon emission performance were successful during this period.

The third observation is that the level of upgrading differs across regions and suggests convergence of the EIs. In general, the environmental performance improvement in regions with a high EI seems a little stronger than for the regions with a low EI. For example, the decline from 2002 to 2012 of the EI in Northeast (from 3.71 to 2.64 tons per 10-thousand RMB) and Central Region (from 3.59 to 2.85 tons per 10-thousand RMB) is larger than that in the coastal regions in the Southeast. Despite this progress in EI reduction, there is still a major gap between Southeast coastal regions and inland regions (especially the Northwest). This suggests that there is room for further upgrading in carbon emission performance.

Table 2

Emission intensities for each final demand category.

Region	2002						2012					
	CSP	FCF	PEX	OEX	WEX	EX	CSP	FCF	PEX	OEX	WEX	EX
Northeast	3.39	4.42	3.40	3.72	3.65	3.75	2.11	2.81	2.45	2.98	2.87	2.92
North Municipalities	1.92	2.73	2.07	2.14	2.12	3.18	0.69	1.24	0.84	1.07	1.04	1.09
North Coast	2.62	4.70	3.03	3.75	3.61	3.64	2.28	3.97	3.27	3.60	3.54	3.59
East Coast	1.98	2.72	1.42	2.12	1.98	2.03	1.43	2.13	1.25	2.03	1.81	2.03
South Coast	1.44	2.08	1.28	2.02	1.72	1.89	1.37	2.26	1.05	1.82	1.60	1.81
Central Region	2.73	4.91	4.51	5.15	5.06	5.18	2.20	3.77	3.21	3.79	3.67	3.88
Northwest	3.80	5.68	5.40	6.27	6.16	6.22	4.88	7.30	6.19	6.67	6.59	6.94
Southwest	2.54	4.80	4.35	4.78	4.70	4.76	1.94	4.08	4.01	4.11	4.10	4.07
China	2.48	4.02	2.01	2.85	2.60	2.78	2.06	3.49	1.87	2.76	2.55	2.70

Notes: CSP = Consumption (by households and governments), FCF = Fixed Capital Formation, PEX = Processing Exports, OEX = Ordinary Exports, WEX = Weighted Export intensity, the EI values in this column are the weighted sums of the EIs in columns PEX and OEX, see eq. (7). All results (except EX) are calculated using the IRIOP tables. EX = Exports, the EI values in this column are obtained by using the traditional inter-regional input-output table without distinguishing processing exports. The values are in tons CO₂ per 10,000 RMB. The results for year 2007 are also available upon request.

4.2. Regional emission intensities for separate final demand categories

The results in Subsection 4.1 were for the EIs at the regional level (calculated as the emissions in region s as embodied in China's final demands divided by value added in region s as embodied in China's final demands). The findings in Dietzenbacher et al. (2012), Su and Ang (2017), and Wang et al. (2020) suggest that the EIs may differ substantially when considered for the separate final demand categories. Table 2 presents the results of the regional and national EIs by final demand category.

The first observation for the EIs is that in almost all cases $FCF > WEX > CSP$. Different final demand categories boost the production in different industries. Investments primarily trigger the production of infrastructure and equipment (e.g., manufacturing of machinery), which are carbon-intensive industries in China with large EIs. The relatively large EIs for exports are partly due to the fact that carbon-intensive manufacturing exports account for a large proportion of China's exports. From a policy point of view, this finding suggests that decreasing regional investment- and export-related EIs will help most to decrease the overall regional EIs.

The second observation is that the EIs of processing exports are smaller than those of ordinary exports, which holds both at the regional and the national level. This is consistent with the finding of Dietzenbacher et al. (2012) at the national level.

The third observation is that for the EIs of exports, it matters whether the IRIOP tables are used or the standard IRIO tables. Following Su and Ang (2017), the EIs in the columns WEX are the weighted sums of PEX and OEX, both obtained by using the IRIOP tables. The results in the columns EX are calculated with the standard IRIO tables (which do not distinguish processing exports). We find $EX > WEX$ for all cases, except for Southwest in 2012, and a large gap for Northern Municipalities. This means that the standard IRIO model overestimates the emission intensities of the exports because it assumes that the two types of processing exports have the same production structure. Because the average production structure resembles the production structure of ordinary exports and because $OEX > PEX$, we have $EX > WEX$ (see Yang et al., 2015). Our results confirm the conclusion that failing to distinguish processing export biases the intermediate input structure, which further biases China's EIs of exports.

The fourth observation is that the findings in Subsection 4.1 on upgrading and downgrading also apply to separate final demand categories. Comparing 2002 and 2012, almost all EIs indicate upgrading, except for Northwest (where all EIs increased, suggesting downgrading). What is not shown in Table 2 is that the carbon emission performance downgraded from 2002 to 2007, which was followed by a larger upgrading from 2007 to 2012. The evolution also shows heterogeneity

Table 3-a

Decomposition results at national level, changes in EI (%) and contributions to these changes (as %), 2002–2012.

China	EI change	λ	T^*	Φ	S	F	e
2002–2012	−9.30	477.1	−311.0	−16.8	−12.4	−26.0	−11.0
2002–2007	17.14	−228.3	276.6	7.3	10.4	24.3	9.6
2007–2012	−22.57	40.9	52.4	−1.9	1.7	5.1	1.8

among regions, with some of the inland regions presenting more upgrading than the coastal regions.

5. Driving factors of China's regional emission intensity evolution

The previous section described China's CO₂ emission intensity evolution both by region and final demand category. However, it did not show to what extent the emission intensities were affected by various driving forces. Employing the multiplicative SDA technique outlined in Section 3 gives the contributions of each driver of the changes in national and regional EIs. The drivers (or determinants) are the changes in: emission coefficients (λ , emissions per unit of output); the technology (T^*); the inter-regional intermediate trade structure (Φ); the substitution effects (S); the domestic final demand structure (F); and the export structure (e). At the regional level, we also distinguish between the intra-regional effects and the inter-regional spillover effects. Table 3 presents our decomposition results for China (Table 3-a) and its eight regions (Table 3-b).

To explain what is in the table, let us consider the results for 2007–2012, in which period China's EI decreased by 22.57%. If only λ had changed (and anything else would have remained the same) the EI would have decreased by 9.83%. Let us denote this as $EI(\lambda) = 0.9007$ (see Appendix C). The other effects are $EI(T^*) = 0.8745$, $EI(\Phi) = 1.0048$, $EI(S) = 0.9957$, $EI(F) = 0.9870$, and $EI(e) = 0.9955$. Note that $EI \text{ change} = 0.7743 = EI(\lambda) \times EI(T^*) \times \dots \times EI(e)$. In order to derive contributions of the drivers that add to 100%, we first take the natural logarithms: $\ln[EI \text{ change}] = \ln[EI(\lambda)] + \ln[EI(T^*)] + \dots + \ln[EI(e)]$. The contribution of the changes in λ to the change in EI (−22.57%) then amounts to $100 \times \ln[EI(\lambda)] / \ln[EI \text{ change}] = 40.9\%$. Note that changes in Φ only would have increased EI. The contribution to the change in EI is −1.9%. So, a negative contribution of a driver means that it would have driven EI to change in the opposite direction as the actual change in EI.

The first observation in Table 3 is that over 2002–2012 the national aggregate EI decreased by 9.30% (indicating mild upgrading) but that it hides a serious contrast. Downgrading took place in 2002–2007 (an

Table 3-b
Decomposition results at regional level, changes in EI (%) and contributions to these changes (as %), 2002–2012.

Region	EI change	λ	$T_{(r)}^*$	$T_{(-r)}^*$	$\Phi_{(r)}$	$\Phi_{(-r)}$	$S_{(r)}$	$S_{(-r)}$	$F_{(r)}$	$F_{(-r)}$	$e_{(r)}$	$e_{(-r)}$
2002–2012												
Northeast	-28.87	150.5	-21.0	-1.6	-17.3	-1.1	0.7	-0.1	14.1	-7.1	-12.0	-5.2
North Municipalities	-37.26	197.9	-78.8	-5.3	-14.2	-0.1	-0.2	-0.1	29.8	-17.5	-6.6	-4.9
North Coast	-13.07	508.0	-457.2	-8.7	45.6	-0.5	4.9	-0.1	105.8	-90.0	15.8	-23.7
East Coast	-23.06	157.1	-87.3	-1.1	22.2	0.6	-12.6	-0.1	30.7	-0.5	-8.1	-0.7
South Coast	-14.15	157.4	-57.7	-3.6	22.8	1.2	-65.2	-0.3	46.8	-2.4	7.2	-6.2
Central Region	-20.78	269.5	-109.9	-5.4	-27.9	-4.9	-0.2	-0.9	53.1	-46.0	-8.5	-18.9
Northwest	26.52	-59.9	87.7	4.2	40.0	7.4	4.1	0.3	-50.9	47.1	3.6	16.4
Southwest	-15.59	273.5	-170.7	-5.9	27.4	-1.4	4.8	-1.8	73.7	-51.5	-29.7	-18.3
2002–2007												
Northeast	-3.44	1375.7	-590.2	-28.3	-155.8	-3.4	-10.7	-1.4	52.2	-424.2	-63.2	-50.7
North Municipalities	-4.22	1628.3	-1051.3	-42.8	-355.6	-5.4	-21.9	-1.6	36.6	-33.4	-3.5	-49.3
North Coast	22.83	-266.5	396.5	5.8	-23.7	-2.1	0.6	0.5	-41.6	10.5	6.1	13.9
East Coast	6.50	-533.1	591.5	8.4	-20.4	-0.2	56.0	0.4	-10.6	14.7	-13.3	6.6
South Coast	12.96	-152.3	167.7	4.5	-20.0	-0.7	101.5	0.1	-33.4	4.9	22.3	5.5
Central Region	8.43	-554.0	480.3	26.6	18.9	4.3	1.0	2.8	-24.0	66.1	31.2	46.9
Northwest	27.29	-55.2	70.8	6.6	32.8	0.9	2.5	0.6	1.0	23.1	4.2	12.6
Southwest	12.76	-226.1	309.8	13.5	-71.3	1.2	2.0	1.3	-46.0	71.6	19.6	24.3
2007–2012												
Northeast	-26.33	10.3	44.2	1.5	-1.4	-0.9	2.1	0.0	9.8	40.7	-6.2	0.0
North Municipalities	-34.50	52.1	20.3	-1.4	20.6	0.4	2.0	0.0	29.1	-15.9	-6.9	-0.4
North Coast	-29.22	47.3	50.6	-0.1	4.4	-1.4	2.3	0.2	18.2	-30.2	10.0	-1.3
East Coast	-27.76	23.4	44.2	0.8	13.9	0.4	0.7	0.0	22.7	2.5	-9.2	0.7
South Coast	-24.00	19.9	42.4	0.0	3.8	0.3	8.8	-0.1	11.2	0.8	13.9	-1.0
Central Region	-26.94	57.1	42.3	2.8	-15.8	-2.5	0.1	0.1	33.2	-17.1	1.7	-1.9
Northwest	-0.60	128.0	-582.1	97.6	-245.4	-250.6	-60.8	13.2	2013.4	-905.5	27.1	-134.9
Southwest	-25.14	66.4	28.5	2.1	-13.6	-0.3	3.6	-0.5	24.1	-0.5	-9.3	-0.6

Notes: The factors contributing to the changes in emission intensity (EI) are: λ , effect of changes in carbon emissions per unit of output; T^* , effect of changes in production technology; Φ , effect of changes in inter-regional intermediate trade structure; S , effect of changes in substitution effect between domestic and imported intermediate inputs; F , effect of changes in domestic final demand structure; e , effect of changes in export structure. Note that the sum of the separate effects equals 100.

increase of EI by 17.14%), followed by considerable upgrading in 2007–2012 (a decrease in EI by 22.57%). The same finding holds for most regions.

The second observation is that two determinants have largely driven the results. Over the entire period, emission coefficients decreased, which led to serious upgrading, contributing 477.1% of the 9.30% decrease in EI. On the other hand, changes in production technology (T^*) led to sizeable downgrading, contributing -310.9% of the 9.30% decrease in EI. The subperiods again sketch two different pictures. In 2002–2007, we observe much upgrading due to improved emission coefficients which was more than nullified by the technology changes so that the overall result was downgrading. In 2007–2012, the upgrading due to improved emission coefficients was much less than that in the period before, but it was accompanied by technology changes that also led to upgrading. Together, they led to substantial upgrading in the second subperiod.

From an industry perspective, the upgrading due to lower carbon emission coefficients can be attributed to the improvement of energy efficiency in some energy industries such as “Petroleum refining, coking and nuclear fuel processing” and “Electricity, gas and water supply”. The energy efficiency improvement meant a significant drop in emissions per unit of output. Because advanced energy-saving and emission-reducing technologies were actively promoted, they were much more used (Zheng et al., 2019). It should be noted that the improvement in energy efficiency works primarily in an indirect way. That is, the production processes of making final products require considerable amounts of intermediate inputs from energy industries and thus affect CO₂ emissions indirectly. Improving the energy efficiency of the high energy-intensive industries contributes a lot to abating CO₂ emissions.

Change in production technology (T^*) was the other major factor that contributed most to the national and regional EIs. They had a strong downgrading effect from 2002 to 2007 and an upgrading effect from 2007 to 2012. This result indicates that China's intermediate input

structure became “dirtier” in the first subperiod and “cleaner” in the second subperiod. This finding is consistent with China's rapid industrialization during 2002–2007, when the GDP share of the secondary industry increased rapidly from 44.5% to 47.6%. In general, the transformation to an industrial economy relies heavily on “dirty” industrial inputs. In the second period 2007–2012, the share of the secondary industry decreased slightly. Instead, the GDP share of the tertiary industry—which generally relies on relatively “clean” intermediate inputs—increased from 42.9% to 45.3%. As a result, changes in overall intermediate inputs increased the EIs during 2002–2007 and reduced them during 2007–2012.

The third observation is the sharp distinction between the Northwest (NW) and the other regions. NW locates in the remote inland area of China. It has a relatively low level of economic development but is rich in mineral resources. Natural gas from the Northwest accounts for about 58% of the national total, NW's coal reserves for nearly 30%, and the region's oil reserves for 23% (Zhou et al., 2018). Due to a continuous improvement of the transportation infrastructure in the western regions, NW has gradually transformed to a resource-based production hub. There are significant carbon transfers between NW and other regions. Our decomposition results reflect this by a clear contribution of the changes in the inter-regional trade of the other regions (i.e. 7.4% for $\Phi_{(-r)}$ in NW) and the changes in the inter-regional spillovers (i.e. 47.1% for $F_{(-r)}$ in NW). Producers in other regions buy more “dirtier” intermediate inputs from NW and domestic consumers rely more on final products from NW. Data for the inter-regional intermediate flows show that 5.8% of China's high-carbon intensive intermediates were sourced from NW in 2002 and this share increased to 10.0% in 2012.

The only other region for which something similar applies is the Central Region (CR). Due to its geographic centrality and well-developed transportation infrastructure, CR plays an important role in providing intermediates for coastal regions. It is kind of a “transmission channel” through which embodied CO₂ emissions flow from inland

regions to coastal regions. Our results show that changes in inter-regional intermediate trade contributed -4.9% (for all other regions the contribution of $\Phi_{(-r)}$ is negligible) to the decrease of EI in this region. The data from the IO tables show that 18.0% of China's high-carbon intensive intermediates were sourced from CR in 2002 and this share increased to 22.0% in 2012. Also changes in inter-regional spillovers had a large increasing effect on the EI of CR, the contribution of $F_{(-r)}$ was -46.0% .

In contrast to NW and CR, coastal regions are more competitive in human resources and focus more on clean industries (like machinery and electronics) and services. We find that changes in inter-regional intermediate trade ($\Phi_{(r)}$) decreased significantly the EIs of coastal regions. This supports the finding that they are "importing" "dirtier" products from inland regions, in particular from CR and NW. The coastal regions are the ones that show clear contributions of the substitution of imported for domestically produced intermediate inputs (i.e. $S_{(r)}$). Coastal regions have better access to foreign markets and use more imported intermediates for production. The emission intensity of China's imported intermediate inputs is generally lower than that of its domestically produced intermediate inputs (Duan and Jiang, 2017). Substitution will therefore increase the emission intensity. We find that, from 2002 to 2012, substitution in South Coast contributed -65.2% to the decrease in the region's EI. In East Coast the contribution of substitution was -12.6% .

As mentioned above, another aim of this paper is to study whether and how processing exports affect the embodied CO₂ emission intensity of exports.⁹ Table 4 presents the decomposition results for embodied EI of exports. The major driving forces for the export-related EI evolution are the changes in the direct emission coefficients and in the production technology. These are the same factors that also drove the changes in regional EIs (in Table 3). However, this SDA shows that processing exports matter for the regional EIs of exports and that its effects show regional heterogeneity. It increased the export EIs for regions with a decreased share of processing exports and, vice versa, decreased for regions with an increased share of processing exports. For example, from 2002 to 2012, the share of processing exports (\mathbf{x}) in South Coast decreased from 65.9% to 50.5% . The export EI of South Coast decreased by 6.86% , and the change in the share of processing export (\mathbf{x}) increased the export EI with its contribution being -63.2% . In contrast, the share of processing export in Central Region increased from 15.2% to 31.2% . This decreased the export EI of Central region and its contribution was 19.3% . These results are in line with the fact that the emission intensity of processing exports is much smaller than that of ordinary exports. Our results confirm that it is very important to differentiate between processing exports and ordinary exports when studying China's export-related questions. Also, at the regional level.

6. Conclusion

This paper analyzed China's emission intensities at the regional level. The results showed that the EIs exhibit clear heterogeneities across the eight regions and across final demand categories. The EIs of coastal regions and the Beijing-Tianjin region are smaller than those of inland regions. In terms of final demand categories, the EIs of investments and exports are larger than those of consumption. The evolution of regional EIs showed that China's regional carbon emission performance experienced "downgrading" first and then "upgrading" during 2002–2012.

⁹ We can also analyze the effect of processing exports on regional EIs using the multiplicative SDA. However, because the share of production of processing exports in total regional production is small (less than 6%), the contribution of changes in processing exports to the changes in regional EIs is limited. We do not present the results here, they are available upon request. Instead, we focus on export-related emissions (like Dietzenbacher et al., 2012; Su et al., 2013; Yan et al., 2020) and explore the effect of changes in processing exports on the embodied EI of exports.

The EI increased for most regions in the period 2002–2007 (which indicates downgrading) and decreased (indicating upgrading) in the period 2007–2012.

We employed an inter-regional input-output based multiplicative SDA to identify the drivers (or determinants) of China's regional EI changes over time. The SDA showed that changes in direct emission coefficients and in production technology were the major driving forces for the EI evolution of most regions. Changes in inter-regional intermediate trade structures and in inter-regional spillover effects exerted different influences on the regional EIs. They decreased the EIs of coastal regions but increased the EIs of inland regions. This finding suggested that the upgraded performance of coastal regions should partly be attributed to the fact that over time these regions imported more "dirtier" products from inland regions. We also distinguished processing exports in the inter-regional input-output table. The results showed that the changes in the share of processing exports had small contributions to the aggregate EIs at national and regional level, but they did matter for the embodied CO₂ EI of exports.

With respect to the reduction of China's regional EIs, our empirical findings point to some policy recommendations. First, measures should be taken to reduce the EI gap between developed coastal regions and other regions. Given that Northwest and Central Region are facing higher levels of EI, it is important to make great efforts to reduce them. Inland regions might adopt local policies (e.g., policies regarding taxes and subsidies) to encourage the upgrading of energy efficiency and production techniques. It is also important for inland regions to stimulate local producers to adopt the energy-saving and cleaner production technologies from the coastal regions.

Second, the upgrading target of inland regions should be one of sharing responsibility with developed coastal regions. Our empirical results show that the central and western regions have been emitting CO₂ for producing "dirty" products that are required by the coastal regions. Therefore, it is necessary for both the central government and local governments to co-ordinate the design and implementation of mechanisms to share the emission-reduction responsibility. For example, establishing an emissions trading system¹⁰ and implementing stricter standards for investments from coastal regions. Other potential measures include establishing a regular exchange system and strengthening the coordination between coastal and inland regions to accelerate the diffusion of cleaner production technologies to inland regions.

Third, it is important to promote the use of cleaner inputs because changes in the production structure appears to a major driving force of the changes in regional EIs. In this aspect, producers could be encouraged to use cleaner, more knowledge-intensive and service-related inputs as a substitute for emission-intensive inputs. In addition, for policy making it is important to distinguish processing exports from ordinary exports at the regional level. From the perspective of emission reduction, processing exports (which are relatively clean) could be given priority in regions (e.g. Northwest and Southwest) with a low share of processing exports.

Our research can be extended in several directions. First, to work with subnational input-output tables that differentiate China's processing exports from ordinary exports, provinces had to be aggregated into regions. Provincial or city level tables, however, may provide additional insights into important emission-related topics. For example, how spillover effects change the emissions of a province or city. Second, the multiplicative SDA in this paper could also be extended to a spatial multiplicative SDA framework that analyzes emission performance disparities across different regions. Lastly, the analysis is not limited to China. The same method can be generalized

¹⁰ This could possibly be achieved by the so-called Domestic Emission Trade System (Cui et al., 2014; Guan and Hubacek, 2010). This scheme uses emission caps and trade permits to effectively link developed coastal regions with inland regions.

Table 4
Decomposition results of changes in China's regional EI for exports, 2002–2012.

Region	Change in EI for exports	λ	T^*	Φ	S	x	h	b
2002–2012								
Northeast	−21.39	251.8	−46.1	3.1	−7.9	−8.8	−59.2	−32.9
North Municipalities	−49.01	223.6	−47.4	−42.2	−3.5	−6.2	−3.2	−21.1
North Coast	−7.55	828.6	−708.6	72.4	−19.1	−24.7	56.9	−105.5
East Coast	−0.44	8980.5	−5908.5	260.0	−1266.3	69.6	−743.0	−1292.2
South Coast	−6.86	216.7	67.9	51.3	−160.4	−63.2	35.9	−48.1
Central Region	−27.05	179.0	−73.9	−6.9	−5.9	19.3	20.2	−31.7
Northwest	16.03	−75.2	93.3	11.7	28.4	16.1	−46.2	71.7
Southwest	−13.78	303.4	−162.0	28.2	−10.2	−3.7	16.0	−71.6
China	−1.57	3154.0	−1563.4	−151.3	−251.6	−254.7	−339.5	−493.5
2002–2007								
Northeast	14.96	−335.6	183.0	49.7	16.5	19.2	96.6	70.7
North Municipalities	1.54	−4559.6	2449.0	1396.7	174.7	151.7	−554.3	1041.9
North Coast	35.72	−159.6	252.9	−35.6	4.0	9.8	−12.4	41.0
East Coast	19.55	−138.6	180.9	−0.6	31.7	−17.6	11.4	32.8
South Coast	20.63	−39.7	41.0	−14.5	70.1	5.7	29.1	8.2
Central Region	3.90	−968.5	904.3	−70.6	58.6	−52.1	−41.7	270.0
Northwest	14.16	−153.1	137.5	49.8	22.7	26.7	−71.3	87.7
Southwest	10.18	−351.1	339.5	−40.0	25.7	17.4	11.3	97.2
China	27.68	−136.8	145.6	8.7	18.3	7.9	20.5	35.9
2007–2012								
Northeast	−31.62	36.3	38.0	20.2	1.0	1.5	−2.0	5.1
North Municipalities	−49.78	117.4	8.0	−10.3	0.4	−2.7	−15.4	2.5
North Coast	−31.88	42.4	56.3	−13.5	−0.7	2.7	1.8	11.1
East Coast	−16.72	80.5	34.5	5.6	0.6	−15.5	−6.8	1.0
South Coast	−22.77	30.6	48.4	3.5	6.9	−13.2	31.0	−7.2
Central Region	−29.79	54.8	31.9	−13.8	1.1	11.6	13.5	0.9
Northwest	1.64	559.2	−265.9	−297.9	74.8	−70.2	158.1	−58.1
Southwest	−21.75	44.7	36.2	1.2	4.0	4.7	14.2	−4.9
China	−22.91	63.5	41.6	−1.0	1.8	−8.1	−1.4	3.7

Notes: The factors contributing to the changes in emission intensity (EI) are: λ , effect of changes in carbon emissions per unit of output; T^* , effect of changes in production technology; Φ , effect of changes in inter-regional intermediate trade structure; S, effect of changes in substitution effect between domestic and imported intermediate inputs; x, effect of changes in the share of processing exports in regional exports; h, effect of changes in the regional pattern of exports; and b, effect of changes in the product composition of exports. Note that the numbers give the percentage contribution of a certain factor (in the column) to the change of the EI for exports (in the row). The sum of the separate contributions in a row equals 100.

to other countries with a high share of processing exports and vast regional disparities, such as Mexico. The analysis could contribute to providing support to establish more effective emission reduction policies.

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Declaration of Competing Interest

The authors declare no competing interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.eneco.2020.104891>.

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