

Outsourcing CO₂ within China

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Recent studies have shown that the high standard of living enjoyed by people in the richest countries often comes at the expense of CO₂ emissions produced with technologies of low efficiency in less affluent, developing countries. Less apparent is that this relationship between developed and developing can exist within a single country's borders, with rich regions consuming and exporting high-value goods and services that depend upon production of low-cost and emission-intensive goods and services from poorer regions in the same country. As the world's largest emitter of CO₂, China is a prominent and important example, struggling to balance rapid economic growth and environmental sustainability across provinces that are in very different stages of development. In this study, we track CO₂ emissions embodied in products traded among Chinese provinces and internationally. We find that 57% of China's emissions are related to goods that are consumed outside of the province where they are produced. For instance, up to 80% of the emissions related to goods consumed in the highly developed coastal provinces are imported from less developed provinces in central and western China where many low-value-added but high-carbon-intensive goods are produced. Without policy attention to this sort of interprovincial carbon leakage, the less developed provinces will struggle to meet their emissions intensity targets, whereas the more developed provinces might achieve their own targets by further outsourcing. Consumption-based accounting of emissions can thus inform effective and equitable climate policy within China.

embodied emissions in trade | regional disparity |
multiregional input-output analysis

As the world's largest CO₂ emitter, China faces the challenge of reducing the carbon intensity of its economy while also fostering economic growth in provinces where development is lagging. Although China is often seen as a homogeneous entity, it is a vast country with substantial regional variation in physical geography, economic development, infrastructure, population density, demographics, and lifestyles (1). In particular, there are pronounced differences in economic structure, available technology, and levels of consumption and pollution between the well-developed coastal provinces and the less developed central and western provinces (2).

In the 2009 Copenhagen Climate Change Conference of the United Nations Framework Convention on Climate Change, China committed to reducing the carbon intensity of its economy [i.e., CO₂ emissions per unit of gross domestic product (GDP)] by 40–45% from 2005 levels and to generating 15% of its primary energy from nonfossil sources by 2020 (3). In the meantime, China's 12th 5-year plan sets a target to reduce the carbon intensity of its economy by 17% from 2010 levels by 2015 (4), with regional efforts ranging from a 10% reduction of carbon intensity in the less developed west and 19% reduction in east coast provinces. Thus, the regions that produce the most emissions and use the least advanced technologies have less stringent intensity targets than the more affluent and technologically advanced regions (5), where the costs of marginal emissions abatement are much higher. In further recognition of such regional inequities, pilot projects are being implemented to test

the feasibility and efficacy of interprovincial emissions trading (6–9). Additionally, progress against emissions targets could be evaluated not only by “production-based” inventories of where emissions occur, but also by “consumption-based” inventories that allocate emissions to the province where products are ultimately consumed (10). Such consumption-based accounting of CO₂ emissions may better reflect the ability to pay costs of emissions mitigation (11).

Details of our analytic approach are presented in *Materials and Methods*. In summary, we track emissions embodied in trade both within China and internationally using a global multiregional input–output (MRIO) model of 129 regions (including 107 individual countries) and 57 industry sectors, in which China is further disaggregated into 30 subregions (26 provinces and 4 cities). Although a number of recent studies have used a similar MRIO approach to assess the emissions embodied in international trade (12–14), studies of emissions embodied in trade within individual countries remain rare due to a lack of data. Here, we use the latest available data to construct input–output tables of interprovincial trade and nest these tables within a global MRIO database. From this framework, we calculate CO₂ emissions associated with consumption in each of the 30 Chinese subregions as well as emissions embodied in products traded between these subregions and the rest of the world (i.e., 128 regions).

Results

In 2007, 57% of China's emissions from the burning of fossil fuels, or 4 gigatonnes (Gt) of CO₂, were emitted during production of goods and services that were ultimately consumed in different provinces in China or abroad. To facilitate reporting and discussion of our results, we group 30 Chinese provinces and cities into eight geographical regions (for details of this grouping, see Fig. 2). Fig. 1, *Upper Left*, shows the largest gross fluxes of embodied emissions among the eight regions, with regions shaded according to net emissions embodied in trade (i.e., the difference between production and consumption emissions) in each region. Beijing–Tianjin, the Central Coast, and the South Coast are the most affluent regions in China, with large imports of emissions embodied in goods from poorer central and western provinces. More than 75% of emissions associated with products consumed in Beijing–Tianjin occur in other regions. Similarly, the Central Coast and South Coast regions outsource about 50% of their consumption emissions.

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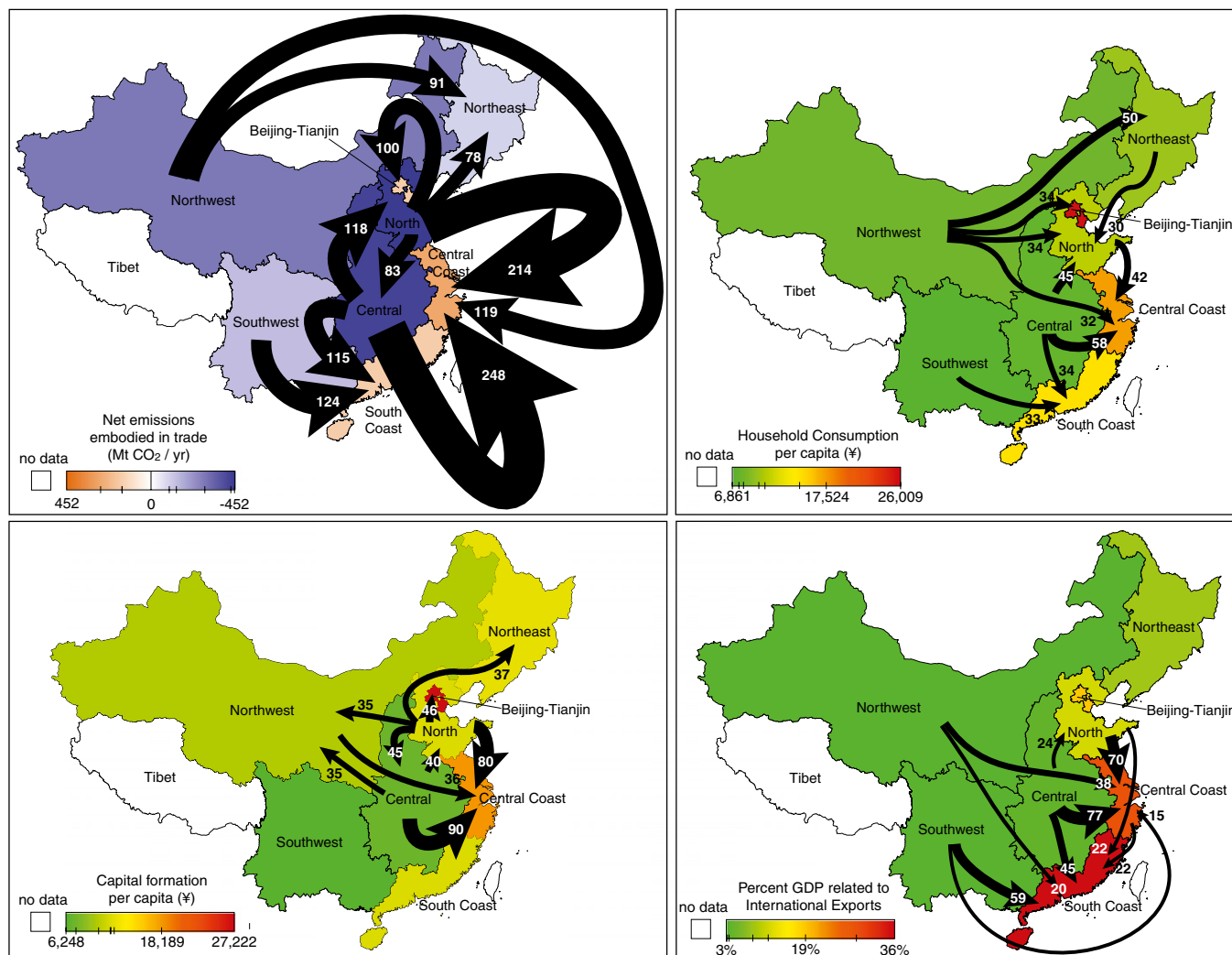


Fig. 1. Upper Left shows largest interprovincial fluxes (gross) of emissions embodied in trade (megatonnes of CO₂ per year) among net exporting regions (blue) and net importing regions (red). Upper Right shows the largest interprovincial fluxes of emissions embodied in products consumed by households, with regions shaded according to value of household consumption per capita (from high in red to low in green). Lower Left shows the largest interprovincial fluxes of emissions embodied in products consumed by capital formation, with regions shaded according to the value of capital formation per capita (from high in red to low in green). Lower Right shows the largest interprovincial fluxes of emissions embodied in products destined for international export, with regions shaded according to the share of GDP related to international exports (from high in red to low in green). Note: carbon fluxes caused by government expenditure are not shown separately in this figure but are included in the total emissions embodied in trade (Upper Left).

The other maps in Fig. 1 highlight emissions embodied in products traded within China that are triggered by different categories of GDP: household consumption (Upper Right), capital formation (Lower Left), and international exports (Lower Right). People living in Beijing–Tianjin, Central Coast, and South Coast provinces have much higher per capita household consumption than do people living in other provinces. For example, household consumption per capita in Beijing–Tianjin in 2007 was more than three times the consumption in the Southwest region. However, our analysis shows that higher levels of household consumption in more developed coastal regions are being supported by production and associated emissions occurring in less developed neighboring regions (Fig. 1, Upper Right). In the case of Beijing–Tianjin, household consumption causes emissions in the Northwest (34 Mt) and North (29 Mt) regions. Similarly, substantial emissions related to household consumption in the Central Coast region are outsourced to the Central (58 Mt), North (42 Mt), and Northwest (32 Mt) regions, and household consumption in South Coast is supported by emissions in the Central (34 Mt) and Southwest (33 Mt) regions. Interestingly,

emissions in the North region support household consumption in more affluent coastal regions, but at the same time, household consumption emissions in the North region are in turn outsourced to the Central (45 Mt) and Northwest (34 Mt) regions.

In keeping with its rapid growth but in contrast to most countries, capital formation (i.e., new infrastructure and other capital investments) in China represents a larger share of GDP (42% in 2007) than household consumption (36% in 2007). In addition, in less-developed western provinces such as Guangxi, Qinghai, Ningxia, and Inner Mongolia, capital formation in recent years has represented an even greater proportion of provincial GDP, for example, more than 70% in 2010. Because such capital formation often entails energy-intensive materials like cement and steel, it is also responsible for a large proportion of China’s emissions: 37% in 2007. The largest transfers of embodied emissions caused by capital formation were to the Central Coast from the Central (90 Mt), North (80 Mt), and Northwest regions (36 Mt); and capital formation in Beijing–Tianjin was supported by substantial emissions produced in the North (46 Mt) (Fig. 1, Lower Left). Partly

in contrast to the dominant pattern of emissions embodied in interprovincial trade for household consumption, the emissions related to capital formation reflect the large-scale expansion of infrastructure that is underway in relatively poor regions such as Southwest and Northwest, such that less developed provinces are in some cases outsourcing emissions to the more affluent regions of eastern China. For example, in 2007 emissions in the North region supported capital formation in the Northwest (35 Mt) and Central (45 Mt) regions.

Previous studies have emphasized international exports as a primary driver of Chinese CO₂ emissions (15–18). According to China's statistical yearbook, 74% of China's exports in 2007 originated in provinces of the Central Coast and South Coast regions (19). However, here we find that 40% of the emissions related to exports from these coastal regions actually occurred in other regions of China (Fig. 1, *Lower Right*). In particular, international exports from the Central Coast region were supported by substantial emissions in the Central (77 Mt), North (70 Mt), and Northwest (38 Mt) regions. Similarly, international exports from the South Coast were supported by large amounts of emissions in Southwest (59 Mt), Central (45 Mt), and Northwest (20 Mt) regions.

Fig. 2 shows the balance of emissions embodied in China's interprovincial and international trade. In provinces in which net export of emissions is large (e.g., Hebei, Henan, Inner Mongolia, and Shanxi), a substantial portion (in those cases, 81–94%) of the emissions embodied in exports were for intermediate (i.e., unfinished) goods traded to other provinces in China. In contrast, 38–54% of the emissions imported to Hebei, Henan, Inner Mongolia, and Shanxi were embodied in finished goods. In Inner Mongolia, exported emissions are also driven by the dominance of energy-intensive heavy industry (more than 70% of that province's gross industrial output in 2007) and coal use (92% of its fuel mix). Meanwhile, Guangdong, Zhejiang, Shanghai, Tianjin, and Beijing are net importers of embodied emissions, with a relatively high proportion of imported emissions embodied in finished goods: from 12% in Zhejiang up to 62% in Tianjin. This shows that the poorer regions export a larger share of low-value-added and import a larger share of high-value products.

Not surprisingly, in each province the emissions embodied in international exports exceeded emissions embodied in imports from other countries in 2007 (Fig. 2). In coastal provinces such as Shandong, Jiangsu, Guangdong, Zhejiang, Shanghai, and Fujian, a considerable fraction of emissions produced support international exports, ranging from 35% to 51% in 2007, whereas for central and western provinces (e.g., Anhui, Hunan, Hubei, Yunnan, Xinjiang), this share is generally less than 25%. However, as discussed above, substantial emissions in these interior provinces are embodied in intermediate goods exported to coastal provinces, where they become part of finished goods for international export.

Fig. 3, row 1, *Left*, shows the largest net domestic importers of embodied emissions produced elsewhere in China, dominated by affluent cities and provinces along the coast such as Zhejiang, Shanghai, Beijing, Guangdong, and Tianjin. The main net domestic exporters of these emissions include mostly less developed provinces in the Central and Northwest regions of China such as Inner Mongolia, Shanxi, and Henan, as well as a few provinces in the North and Northeast regions such as Hebei, Shandong, and Liaoning. Normalizing net domestic imports of emissions per unit of GDP (Fig. 3, row 1, *Center*) and per capita (Fig. 3, row 1, *Right*) further emphasizes the disproportionate outsourcing of emissions from rich coastal cities such as Shanghai, Beijing, and Tianjin. In the case of net domestic exports of emissions per unit GDP (Fig. 3, row 2, *Center*), we find that the carbon intensity of net domestic exports is greatest in Inner Mongolia (247 g of CO₂ embodied in net exports per ¥GDP), Shanxi (164 g per ¥GDP), and Hebei (144 g per ¥GDP) due to the prevalence of heavy industry and/or energy products (i.e., coal and electricity) exported from these provinces.

Overall consumption-based emissions are greatest in large and rich coastal provinces such as Shandong, Jiangsu, Guangdong, Zhejiang, Hebei, Liaoning, and Shanghai, as well as populous provinces such as Henan and Sichuan (Fig. 3, row 3, *Left*). However, the provinces with the lowest consumption-based emissions include the least developed provinces in the Central, Northwest, and Southwest regions as well as cities or provinces with relatively small populations (e.g., Tianjin) (Fig. 3, row 4, *Left*). However, the consumption-based carbon intensity (emissions per unit GDP) is

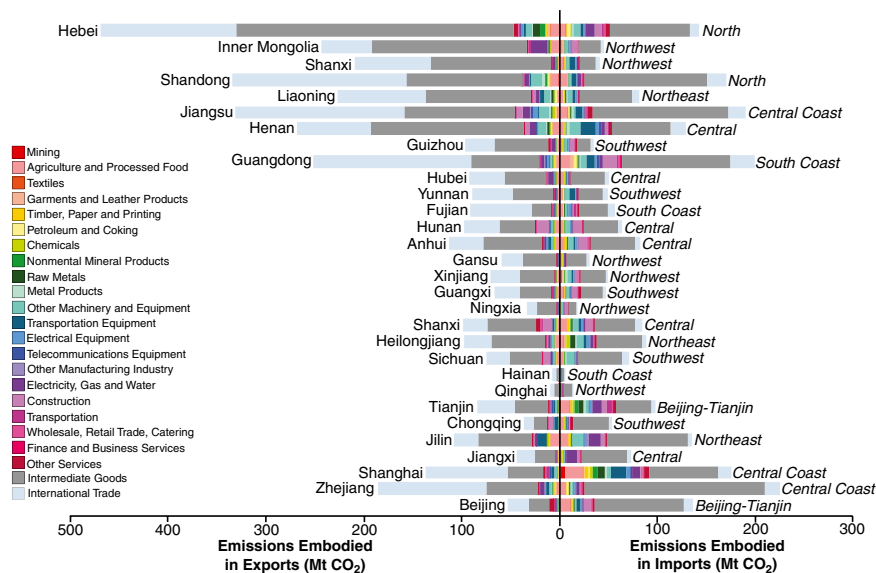


Fig. 2. Emissions embodied in interprovincial and international trade for 30 provinces. Colors represent trade in domestic finished goods by industry sector. Traded domestic intermediate goods (dark gray) are those used by industries in the importing provinces to meet consumer demand for domestic goods. Internationally traded goods (light gray) are those goods purchased from or sold to international markets. Italicized labels at the right of each bar indicate to which of the eight aggregated regions the province or city has been assigned.

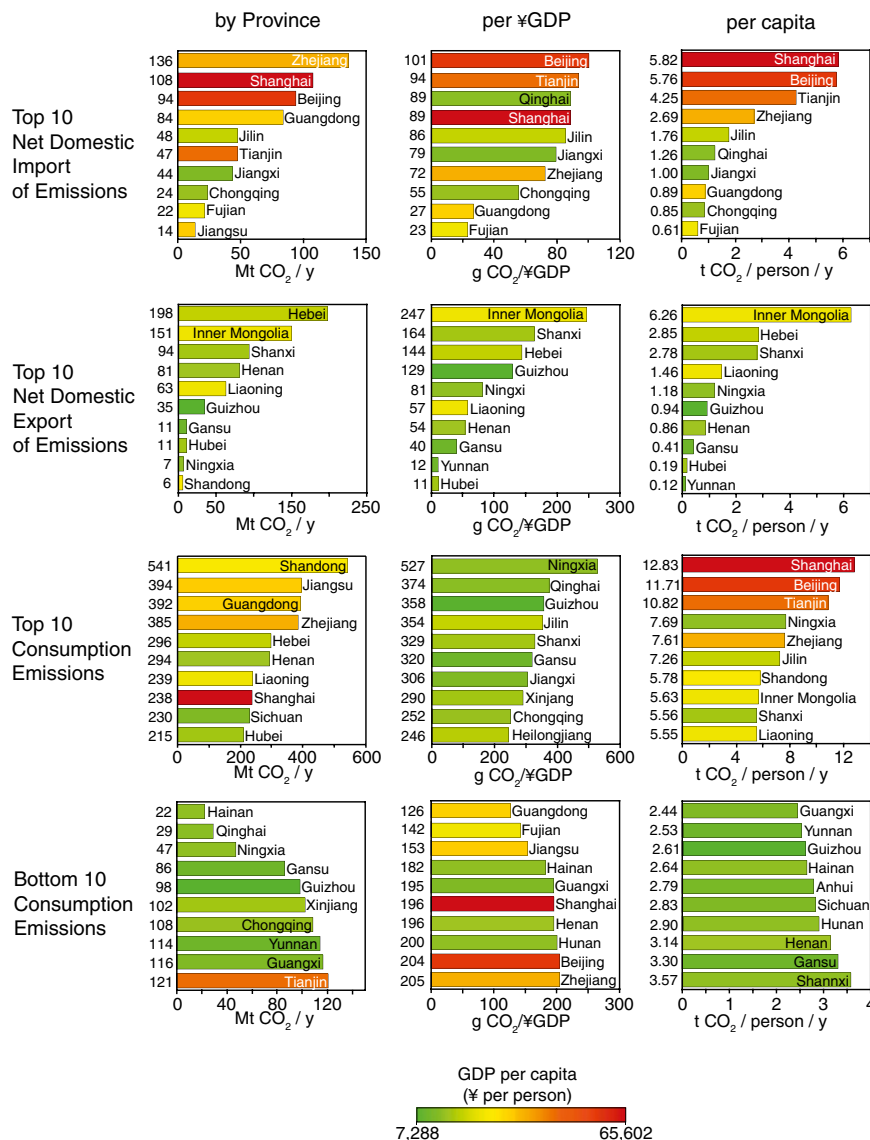


Fig. 3. The top 10 provinces by net domestic imports (row 1), net domestic exports (row 2), and consumption emissions (row 3), and the bottom 10 provinces by consumption emissions (row 4), all presented as regional totals (left column), per unit GDP (center column), and per capita (right column). The color of bars corresponds to provincial GDP per capita from the most affluent provinces in red to the least developed provinces in green (see scale).

greatest in provinces of the Central, Northwest, and Southwest regions where coal use and energy-intensive activities such as the production of capital infrastructure are dominant, and economies are growing rapidly (Fig. 3, row 3, *Center*). In contrast, the high GDP and more established economies in coastal provinces are among the least carbon intensive (Fig. 3, row 4, *Center*). For example, Ningxia, in the less developed Northwest region, has the highest consumption-based carbon intensity, 527 g of CO₂ per ¥GDP, which is more than four times the intensity of Guangdong, in the rich South Coast region, where carbon intensity reaches a low level of 126 g of CO₂ per ¥GDP. Similarly, per capita consumption-based carbon emissions in the most affluent cities of Shanghai, Beijing, and Tianjin (10.8–12.8 tons per person; Fig. 3, row 3, *Right*) are more than four times that of interior provinces such as Guangxi, Yunnan, and Guizhou (2.4–2.6 tons per person; Fig. 3, row 4, *Right*).

Discussion

Our results demonstrate the economic interdependence of Chinese provinces, while also highlighting the enormous differences

in wealth, economic structure, and fuel mix that drive imbalances in interprovincial trade and the emissions embodied in trade. The highly developed areas of China, such as Beijing–Tianjin, Central Coast, and South Coast regions, import large quantities of low value-added, carbon-intensive goods from less developed Chinese provinces in the Central, Northwest, and Southwest regions. In this way, household consumption and capital formation in the developed regions, as well as international exports from these regions, are being supported by emissions occurring in the less developed regions of China (20). Indeed, the most affluent cities of Beijing, Shanghai, and Tianjin, and provinces such as Guangdong and Zhejiang, outsource more than 50% of the emissions related to the products they consume to provinces where technologies tend to be less efficient and more carbon intensive.

The carbon intensity of imports to the affluent coastal provinces is much greater than that of their exports—in some cases by a factor of 4, because many of these imports originate in western provinces where the technologies and economic structure are energy intensive and heavily dependent on coal. Provinces such

as Inner Mongolia and Shanxi, which together produce more than 80% of coal burned in China and export 23% and 36% of the electricity they generate to other provinces, respectively, are locked into energy- and carbon-intensive heavy industries that account for more than 80% of their total industrial output.

At present, China's carbon policy seeks to address regional differences within China by setting higher targets for reducing emissions in Central Coast (reduction by 19%), Beijing–Tianjin (18–19%), South Coast (17.5–19.5%), except Hainan (11%), which is a tourist region, and North (18%); medium targets in Northeast (16–18%) and Central (17%); and lower targets in Northwest (10–16%) and Southwest (11–17.5%) by 2015 (4). However, provinces in the central and western parts of China will struggle to achieve even these more modest reduction targets if no funds are provided for updating their infrastructure and importing advanced technologies. Moreover, the more ambitious targets set for the coastal provinces may lead to additional outsourcing and carbon leakage if such provinces respond by importing even more products from less developed provinces where climate policy is less demanding.

However, the marginal cost of emissions reductions are substantially lower in interior provinces such as Ningxia, Shanxi, and Inner Mongolia, where produced emissions, energy intensity, and coal use are all high relative to the cities and provinces along the central coast. The emissions trading scheme being tested now (6) may help achieve least cost emissions reductions through technology transfer and capital investment from the coast to the interior. However, this study provides another justification for such a scheme: the economic prosperity of coastal provinces is being supported by the industry and carbon emissions produced in the central and western provinces. For instance, if a uniform price were imposed on carbon within China, larger emissions reductions would occur in western provinces where marginal costs are lower, and the cost of these reductions would be shared by affluent consumers in coastal China who would pay more for the goods and services imported from the interior. In contrast, more lenient intensity targets in the western provinces will necessitate more expensive emissions reductions in coastal provinces, and will encourage additional outsourcing to the western provinces. Consumption-based accounting can thus inform effective and equitable policies to reduce Chinese CO₂ emissions.

Materials and Methods

In this study, we include 26 provinces and 4 cities (in total, 30 regions) except Tibet and Taiwan. The results are based on 30 regions, but for easier understanding the results and discussions are organized in 8 Chinese regions: Northeast (Heilongjiang, Jilin, Liaoning), Beijing–Tianjin (Beijing, Tianjin), North (Hebei, Shandong), Central (Henan, Shanxi, Anhui, Hunan, Hubei, Jiangxi), Central Coast (Shanghai, Zhejiang, Jiangsu), South Coast (Guangdong, Fujian, Hainan), Northwest (Inner Mongolia, Shanxi, Gansu, Ningxia, Qinghai, Xinjiang), and Southwest (Sichuan, Chongqing, Yunnan, Guizhou, Guangxi).

The 2007 input–output tables (IOTs) for each of China's 30 provinces except Tibet are compiled and published by the National Statistics Bureau (21). The official IOTs have 42 sectors and the final demand category in the tables consists of rural and urban household consumption, government expenditure, capital formation, and exports. The IOTs also report the total value, by sector, that is shipped out of each province and the total value, also by sector, that enters into each destination province. This set of sector-level domestic trade flow data provides the basis for constructing the interregional trade flow matrix with both sector and province dimensions. In terms of the core methodology for the construction, we adopt the best-known gravity model of Leontief and Strout (22) and augment it in line with LeSage and Pace (23) and Sargento (24) to accommodate the spatial dependences of the dependent variable. Because the calibration of the augmented gravity model for each sector needs a known trade matrix of dominant/representative commodities in the sector (e.g., grain and cotton in the agricultural sector) and because such detailed data are not available for some small sectors, we aggregate the provincial tables into 30 sectors to accommodate this data constraint.

In the standard Leontief–Strout gravity model, the sector-specific interregional trade flows are specified as a function of total regional outflows,

total regional inflows, and the cost of transferring the commodities from one region to another. This cost is typically proxied by a distance function. In the augmented gravity model, the equation also includes three variables reflecting the spatial dependences of the dependent variable: The origin-based one is defined as the spatially weighted average of flows from the neighbors of each region of origin to each destination region; the destination-based one is the spatially weighted average of flows to the neighbors of each destination regions, which are from the same region of origin; the mixed origin–destination–based one is defined as the spatially weighted average of flows from the neighbors of each region of origin to the neighbors of each destination region. The mathematical simplicity and intuitive nature of the gravity model and more importantly the reasonability of its empirical results grant it popularity and success in calibrating trade flows (25, 26). The comparative assessment of Sargento (24, 27) on alternative models further indicates that the gravity model is well suited to explain trade flow behavior. A technical specification of our augmented gravity model is presented in *SI Text 1*.

We run regressions of the augmented gravity model based on the known trade matrix of dominant/representative commodities in 5 primary sectors, 16 manufacturing sectors, and 1 electricity sector. The regressions for agriculture, chemistry, and electronics are presented in *SI Text 1* as three illustrative examples. The regressions give us the estimated values of the model parameters. Substitution of the known values of the total regional outflows, total regional inflows, and distance function into the augmented gravity model with known parameters gives us the initial trade matrix for the 5 primary sectors (sectors 1–5), 16 manufacturing sectors (sectors 6–21), and 1 electricity sector (sector 22). For gas and water production (sector 23), construction (sector 24), and all service sectors (sectors 25–30), we do not have qualified sample data of dominant/representative commodities. To get the initial matrix for these sectors, a simple data pooling method of Hulu and Hewings (28) is adopted with an augmentation as follows. Sixty percent of the outflow of each province is distributed to other provinces in proportion to the inverse of distance, and the remaining 40% is distributed according to the ratio of a province's inflow to the sum of all provinces' inflows. The initial trade flow matrix produced above, which excludes intraregional flows, does not meet the "double sum constraints" in that the row and column totals match with the known values given in the 2007 IOTs. To assure agreement with the sum constraints, we apply the well-known iterative procedure of biproportional adjustment of the RAS technique. The RAS procedure tends to preserve as much as possible the structure of the initial matrix, with the minimum amount of necessary changes to restore the row and column sums to the known values (29, 30). To complete with the system boundary, we connect the Chinese MRIO 2007 to global trade database version 8 (based on 2007 trade data) published by Global Trade Analysis Project (GTAP) (31) (description of connecting to the GTAP database is included in *SI Text 2*).

China does not officially publish annual estimates of CO₂ emissions. We estimate CO₂ emissions of the 30 provinces based on China's provincial energy statistics. We adopt the Intergovernmental Panel on Climate Change reference approach (32) to calculate the CO₂ emissions from energy combustion as described by Peters et al. (17) and applied in previous work on China by three of the authors (2, 15, 16). We applied the method to calculate emissions for all provinces in 2007. The inventories include emissions from fuel combustion and cement production. Total energy consumption by production sectors and residents provide the basis for calculating the energy combustion CO₂ emissions (21). We construct the total energy consumption data for production purposes based on the final energy consumption (excluding transmission energy loss), plus energy used for transformation (primary energy used for power generation and heating) minus nonenergy use. The transmission energy loss refers to the total of the loss of energy during the course of energy transport, distribution, and storage, and the loss caused by any objective reason in a given period (26). The loss of various kinds of gas due to discharges and stocktaking is excluded (26). We understand there are two different official and publicly available energy data sources in China between provincial and national statistics and the discrepancy is up to 18% (33). We adopted the provincial energy statistics to compile the emission inventories for every Chinese province as it more closely represents energy consumption at the provincial level.

In a MRIO framework, different regions are connected through interregional trade. The technical coefficient submatrix $A^{rs} = (a_{ij}^{rs})$ is given by $a_{ij}^{rs} = z_{ij}^{rs} / x_j^s$, in which z_{ij}^{rs} is the intersector monetary flow from sector i in region r to sector j in region s ; x_j^s is the total output of sector j in region s . The final demand matrix is $F = (f_i^{rs})$, where f_i^{rs} is the region's final demand for goods of sector i from region r . Let $x = (x_j^s)$. Using familiar matrix notation and dropping the subscripts, we have the following:

$$A = \begin{bmatrix} A^{11} & A^{12} & \dots & A^{1n} \\ A^{21} & A^{22} & \dots & A^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A^{n1} & A^{n2} & \dots & A^{nn} \end{bmatrix}; F = \begin{bmatrix} f^{11} & f^{12} & \dots & f^{1n} \\ f^{21} & f^{22} & \dots & f^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f^{n1} & f^{n2} & \dots & f^{nn} \end{bmatrix}; x = \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^n \end{bmatrix}.$$

Consequently, the MRIO framework can be written as follows: $x = Ax + F$, and we have $x = (I - A)^{-1}F$, where $(I - A)^{-1}$ is the Leontief inverse matrix, which captures both direct and direct inputs to satisfy one unit of final demand in monetary value; I is the identity matrix. To calculate the embodied emissions in the goods and services, we extend the MRIO table with

environmental extensions by using CO₂ emissions as environmental indicator: $CO_2 = k(I - A)^{-1}F$, where CO₂ is the total CO₂ emissions embodied in goods and services used for final demand; k is a vector of CO₂ emissions per unit of economic output for all economic sectors in all regions. The application detail of the MRIO framework to our research is presented in [SI Text 1](#).

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Supporting Information

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SI Text

SI Text 1. Construction of Multiregion Input–Output Model for Chinese Provinces. *Key notions and basic equations of the multiregion input–output model.* In this study, we construct a multiregion input–output (MRIO) model for 30 regions within China. Assuming that there are n production sectors and p geographic regions in the economy, z_i^{rs} denotes the monetary flow of good i from region r (the origin) to region s (the destination). The total shipments of good i into region s from all of the regions in the model is denoted by T_i^s :

$$T_i^s = \sum_{r=1}^p z_i^{rs}. \quad [\text{S1}]$$

The proportion of product i used in region s that comes from region r is expressed as follows:

$$c_i^{rs} = z_i^{rs} / T_i^s, \quad [\text{S2}]$$

where c_i^{rs} is called the trade coefficient. For each possible origin–destination pair of regions, we construct c^{rs} as follows:

$$\hat{c}^{rs} = \begin{bmatrix} c_1^{rs} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & c_n^{rs} \end{bmatrix}, \quad [\text{S3}]$$

in which the elements show, for region s , the proportion of the total amount of each good used in region s (column) that comes from region r (row).

Linking the above notation to the one used in standard input–output modeling, the total output of sector i , x_i^r can be expressed as follows:

$$x_i^r = \sum_{j=1}^n z_{ij}^{rr} + \sum_{\substack{s=1 \\ s \neq r}}^p \sum_{j=1}^n z_{ij}^{rs} + f_i^r, \quad [\text{S4}]$$

in which f_i^r is the intraregional sale of sector i to final demand. The regional input–output technical coefficient is given by the following:

$$a_{ij}^{rr} = z_{ij}^{rr} / x_j^r. \quad [\text{S5}]$$

Furthermore, let

$$A = \begin{bmatrix} A^1 & 0 & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 \\ 0 & 0 & A^r & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & A^p \end{bmatrix},$$

$$f = \begin{bmatrix} f^1 \\ \vdots \\ f^r \\ \vdots \\ f^p \end{bmatrix},$$

$$x = \begin{bmatrix} x^1 \\ \vdots \\ x^r \\ \vdots \\ x^p \end{bmatrix}, \text{ and}$$

$$C = \begin{bmatrix} \hat{c}^{11} \dots \hat{c}^{1s} & \dots & \hat{c}^{1p} \\ \vdots & \ddots & \vdots \\ \hat{c}^{r1} \dots \hat{c}^{rs} & \dots & \hat{c}^{rp} \\ \vdots & \ddots & \vdots \\ \hat{c}^{p1} \dots \hat{c}^{ps} & \dots & \hat{c}^{pp} \end{bmatrix}$$

such that $A^r = (a_{ij}^{rr})$ is a matrix of intraregional technical coefficients in region r ; $f^r = (f_i^r)$ is a vector of final demand; $x^r = (x_i^r)$ is a vector of total sectoral output. Then, the basic accounting relations in the full MRIO model can be summarized as follows:

$$x = CAx + Cf. \quad [\text{S6}]$$

Augmented gravity model for estimating the initial matrix of interregional trade flows. First, we introduce the basic gravity model, which takes inspiration directly from Newton's observation on gravity:

$$y_i^{rs} = e^{\beta_0} \frac{(x_i^{rO})^{\beta_1} (x_i^{Os})^{\beta_2}}{(d^{rs})^{\beta_3}}, \quad [\text{S7}]$$

where y_i^{rs} represents trade flows of sector i from province r to province s ; e^{β_0} is the constant of proportionality; x_i^{rO} is the total outflows of sector i from province r , x_i^{Os} is the total inflows of sector i to province s , and both x_i^{rO} and x_i^{Os} are known from statistics; d^{rs} is the distance between province r and s (in this study, we use distance between the capital cities of two provinces); β_1 and β_2 are weights assigned to the masses of origin and destination, respectively; β_3 is the distance decay parameter. Eq. S7 can be transformed into Eq. S8,

$$\ln(y_i^{rs}) = \beta_0 + \beta_1 \ln(x_i^{rO}) + \beta_2 \ln(x_i^{Os}) - \beta_3 \ln(d^{rs}) + \varepsilon, \quad [\text{S8}]$$

and further into Eq. S9:

$$Y = \beta_0 L_n + \beta_1 X_1 + \beta_2 X_2 - \beta_3 X_3 + \varepsilon, \quad [\text{S9}]$$

where Y is a $N \times 1$ matrix that represents the logarithm of the trade flow of product i between regions; L_n is a $N \times 1$ matrix with all elements equal to 1; X_1 and X_2 represent the logarithm of the total outflows from origin regions and total inflows to destination regions, respectively; X_3 is the distance between two regions.

Although the basic gravity model attempts to model the interdependence among observations using distance, this attempt is regarded as being inadequate for trade flow data because regions typically influence the trade of their neighbors. For instance, LeSage and Pace (1) show that the spatial dependence of the dependent variable can be viewed as either a long-run equilibrium of an underlying spatiotemporal process, or a result of omitted variables that exhibit spatial dependence. More intuitively speaking, forces leading to exports from any origin to a particular destination region may induce similar exports from the neighbors of this origin to the same destination. This is called origin-based spatial

dependence. Similarly, forces leading to imports to any destination from a particular origin may induce similar imports to the neighbors of this destination from the same origin. This is called destination-based spatial dependence. The mixed origin-destination-based spatial dependence means that flows from region r to regions s are influenced by the average of flows from all of the neighbors of r to all of the neighbors of s , in addition to other factors specified in the basic gravity model (1, 2). Incorporation of these three types of spatially lagged dependent variables into Eq. S9 gives the following:

$$Y = \rho_0 W_0 Y + \rho_d W_d Y + \rho_w W_w Y + \beta_0 L_n + \beta_1 X_1 + \beta_2 X_2 - \beta_3 X_3 + \varepsilon, \quad \text{[S10]}$$

where $W_0 = W \otimes I$, $W = (w^{rs})$ is a row-normalized $N \times N$ matrix of spatial weights between provinces with all elements on the diagonal equals to 0, I is the identity matrix, and \otimes denotes the Kronecker product. Thus, the first spatially lagged dependent variable, $W_0 Y$, is the spatially weighted average of flows from the neighbors of each origin region to each of the destinations and captures the origin-based spatial dependence of trade flows. $W_d = I \otimes W$ and $W_d Y$ is the spatially weighted average of flows to the neighbors of each destination, which are from the same origin region and captures the destination-based spatial dependence. $W_w = W \otimes W$ and $W_w Y$ is the spatially weighted average of flows from the neighbors of each origin to the neighbors of each destination and captures the mixed origin-destination-based spatial dependence of trade flows.

For the specification of distance function, which in turn defines the spatial weights, we adopt the Gaussian function as a continuous and monotonically decreasing function to represent the relationship between spatial weight w^{rs} and distance d^{rs} . It can be expressed as follows:

$$w^{rs} = \exp\left(-\frac{1}{2}(d^{rs}/b)^2\right), \quad \text{[S11]}$$

in which b represents the bandwidth, a nonnegative decay parameter regulating the relationship between spatial weights and distances. For a given bandwidth, when d^{rs} is equal to 0, w^{rs} is equal to 1. With the increase of d^{rs} , w^{rs} decreases gradually. The broader (narrower) the bandwidth (b), the slower (faster) the decay rate of the spatial weights (w^{rs}) with the increase in distance. In this research, selection of bandwidths is industry specific. For some industries such as agricultural products and food manufacturing, trade flows are dominated by those between regions in close proximity, and thus the bandwidth should be smaller. For other industries such as steel products and electronics, trade flows extend over long distances, and thus the bandwidth should be larger. Spatial weight matrix W can be generated after the bandwidth is set, with all diagonal elements being equal to zero.

The parameters of Eq. S10 are first estimated econometrically using sample data, and then we estimate an initial matrix of trade flows as follows:

$$\hat{Y} = (I - \hat{\rho}_0 W_0)^{-1} (I - \hat{\rho}_d W_d)^{-1} (\hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 - \hat{\beta}_3 X_3). \quad \text{[S12]}$$

Data sources for estimating the initial matrix of interregional trade flows. Data on the total value of products exported from each origin province and that imported to each destination province by sector are from the 2007 provincial input-output tables (IOTs), which are compiled and published by the State Statistical Bureau of China. Distance between two provinces is measured by the average of railway distance and highway distance between the capital cities of provinces. Sample data on interprovincial trade flows in 5 primary sectors (sectors 1–5), 16 manufacturing sectors (sectors 6–21), and electricity sector (sector 22) are collected mainly from the statistics on flows of bulk commodities compiled by the Ministry of Transport and the Ministry of Railways of China, supplemented

by price and other data compiled by various ministries and state-owned large trading companies. For example, flows of grains and cotton are used as the sample data for the agricultural sector, flows of chemical fertilizers and pesticides are used as the sample data for the chemical sector, and flows of steel and nonferrous metal are adopted as the sample data for the electronics sector. The data on trade flows of bulk commodities are typically in physical units (e.g., tons) and so are converted to values using commodity price data. Table S1 presents the list of 30 economic sectors. Fig. S1 shows the interprovincial trade flows of the sample data of the agriculture sector.

To keep observations with zero value after the logarithm transformation as required in Eq. S8, we replace zeros with a very small value, which is set to be 0.001 times the minimum value of all observations for the variable concerned. In the final result-report stage, we return such small values to zero.

Three examples of regressions and the corresponding sensitivity analyses.

We estimate the parameters and assess errors in the basic gravity model Eq. S9 by least squares and in the augmented model Eq. S10 by spatial maximum likelihood (ML). For an intuitive comparison between two models, we calculated R^2 and F test for the spatial ML regressions. Table S2 reports the comparative results for the agricultural, chemical, and electronics sectors as three illustrative examples. The results show that the estimations of the augmented gravity model have much higher values of R^2 and also more significant levels of F test across all three sectors in comparison with those resulting from the estimations of the basic gravity model. In terms of t statistics, coefficients on all spatially lagged variables are highly significant and have the expected signs (note that $\hat{\rho}_w = -\hat{\rho}_d$, as implied in Eq. S11). These results mean that interregional trade flows are significantly spatial dependent. More interestingly, although the statistical significance of the coefficients on total outflow and total inflow of agricultural and chemistry products in the basic gravity model are replaced by that of the coefficients on three spatially lagged Y variables in the augmented gravity model, for the electronics sector, this replacement of significant levels takes place only for the total outflow variable and the coefficient on the total inflow variable X_2 is highly significant. This comparison indicates that the interprovincial trade in agricultural and chemical goods decays very rapidly with distance (Eq. S11) and is thus dominated by trade between close neighbors, whereas imports of electronic goods take place over longer distances.

Table S3 reports in more detail the top 15 origin-destination pairs of trade flows in the three example sectors. For the agricultural sector, the table shows that 8 of the 15 pairs are next-door neighbors (numbers 1–3, 9, 11, 14) or next-door-but-one neighbors (numbers 12 and 15). In addition, Shandong is the destination in five cases (rows 2, 4, 6, 9, and 10) because food processing there accounts for one-fifth of the national total output and the province thus imports agricultural goods from throughout China. Similarly, Shanghai appears three times because it is a city with a huge population and also a center for light industry, and must import agricultural products from other provinces. Textile production in Jiangsu and Zhejiang account for 40% of the national total output, and these two provinces import large quantities of fiber products from other provinces. Some provinces, such as Henan and Sichuan, have a very large agricultural sector but are neither a major destination nor origin for agricultural trade because these provinces have a large population and thus consume much of what is produced within their borders. Xinjiang is an exception to the rule of proximity because it is a major exporter of agricultural products, mainly cotton and fruits to which its climate is particularly well suited.

The top 15 origin-destination pairs in the chemical sector are also dominated by the flows between next-door neighbors (rows 1, 4, 5–7, 10, 12–15) and next-door-but-one neighbors (rows 2, 8, and 11). The majority of these provinces are located in the Yangtze River Delta and Pearl River Delta regions and Northeast China. It is because Jiangsu, Guangdong, Shanghai, and Zhejiang are major

producers of chemical goods. They together produce 45.6% of the national output and account for 46.2% and 30.6% of the national total inflows and outflows, respectively. In addition, the three provinces in the Northeast region are the traditional base for heavy industry in China. Our results are consistent with these well-established observations.

In contrast to the cases of agriculture and chemical goods, the top 15 origin–destination pairs are no longer dominated by next-door or next-door-but-one neighbors in the electronics sector. The pairs of Shanghai–Guangdong and Jiangsu–Guangdong are the top two pairs with a scale of the trade flows much higher than that of row 3 but they are neither the next-door or next-door-but-one neighbor pairs. In fact, among the top eight pairs, only in row 3 (Fujian–Guangdong) is the pair made up of close neighbors. Instead, imports and exports in the sector are dominated by trade between Guangdong, Shanghai, and Jiangsu, reflecting the fact that these three provinces account for 50.6% of the national total output of electronics production.

Sensitivity analysis of the bandwidth. The bandwidth b in Eq. S11 is a nonnegative decay parameter, which regulates the relationship between spatial weights and distances, regulating the decay rate of spatial dependence but not the direction and major structure of the flows. We tested the sensitivity of regional trade regressions in each sector to this parameter, and Table S4 reports the results of the sensitivity analysis in the agricultural sector as an example. In the case of the agricultural sector, we use two bandwidths, $b = 1,000$ and $b = 500$. Table S4 shows that, with the narrower bandwidth (the effect of spatial dependence decays more quickly with distance) $b = 500$, the scales of trade flows between the top origin–destination pairs are all increased with only one exception (row 5), together with a moderate changes in the ranks of pairs. For example, the scale of trade between the row 1 pair (Hunan to Guangdong) increases from renminbi (RMB) 20.6 billion under $b = 1,000$ to RMB 33.1 billion under $b = 500$; and that between the row 2 pair under $b = 500$ is RMB 23.9 billion (Heilongjiang to Shandong), 4.9 billion higher than that between the row 2 pair under $b = 1,000$ (Hebei to Shandong). The dominant trade directions do not change and the observed shifts in rankings are not surprising. Thus, the effect of the narrower bandwidth, to increase the decay rate of spatial dependence, increases the extent of trade concentration in the expected way.

SI Text 2. Linking China's MRIO to GTAP. To extend the system boundary, we connect the MRIO model of Chinese provinces to a global MRIO model (G-MRIO), which is based on version 8 of the Global Trade Analysis Project (GTAP) database, which describes bilateral trade patterns, production, consumption, and intermediate use of commodities and services among 129 regions for 57 industry sectors for the years 2004 and 2007 (3). The G-MRIO was constructed following the method described in more detail by Peters et al. (4). Because China is one of the 129 GTAP regions, we then disaggregated the Chinese IOT in GTAP into 30 province-level tables according to the IOTs within our Chinese MRIO model. GTAP's international import and export matrices for China were also disaggregated and allocated to the 30 provinces according to our data on provincial exports and imports assuming that the international exports of each sector in a province are distributed among importing sectors in foreign countries in the same proportion as China's total exports. We make a converse assumption that provincial international import matrices are sourced from countries in the same proportion as total Chinese imports. Altogether, then, our G-MRIO resolves im-

ports and exports among 128 countries and 30 Chinese provinces with 57 sectors for foreign countries and 30 sectors for Chinese provinces.

SI Text 3. Compiling CO₂ Emissions Inventories for China's 30 Provinces. Estimations of CO₂ emissions for Chinese 30 provinces are based on China's provincial energy statistics. We adopt the Intergovernmental Panel on Climate Change (IPCC) reference approach (5) to calculate the CO₂ emissions from energy combustion. Compiling provincial CO₂ emissions inventories accounts for three parts as follows:

Part 1: CO₂ emissions from fuel combustion.

$$\text{Combustion CO}_2 = E \times V \times F \times O.$$

E : the amount of energy combustion from different fuel types¹ (in physical units). $E = \text{Total final consumption}^1 + \text{energy used for thermal power}^1 + \text{energy used for heating}^1 - \text{non-energy use}^1$

V : Chinese specific low-calorific value of different fuel types² (generally lower than the IPCC default value suggested in the literature).

F : Emission factors of different fuel types³.

O : Chinese specific oxidization rate^{4,5} (vary among both fuel types and difference final use; generally lower than IPCC default value to avoid overestimated of CO₂ emission).

Part 2: CO₂ emissions from cement production.

$$\text{Process CO}_2 = \text{Cement(including clinker)production amount}^6 \times \text{Emission factor}^3.$$

Part 3: CO₂ emissions from international bunker.

$$\text{Bunker fuel CO}_2 = E' \times V \times F \times O.$$

E' : The amount of China airplanes and ships refueling abroad minus the amount of foreign airplanes and ships refueling in China¹, E' includes fuel types of gasoline, kerosene, diesel oil, fuel oil, and liquefied petroleum gas.

Data sources.

1. Chinese Energy Statistics Yearbook 2008, Energy Balance Table (6).
2. Chinese Energy Statistics Yearbook 2008, Appendix, Conversion Factors from Physical Units to Coal Equivalent (6).
3. Intergovernmental Panel on Climate Change, 2006 IPCC Guidelines for National Greenhouse Gas Inventories (5).
4. China Climate Change Country Study (7).
5. The People's Republic of China National Greenhouse Gas Inventory (8).
6. Chinese Statistics Yearbook 2008, Table 14-23, Output of Industrial Products by Region (9).

The full datasets of CO₂ emission inventories for 30 Chinese provinces in 2007 can be found in the supplementary information of the study by Guan et al. (10).

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3. Global Trade Analysis Project (2012) *GTAP 8 Data Base* (Global Trade Analysis Project).
 4. Peters GP, Andrew R, Lennox J (2011) Constructing an environmentally-extended multi-regional input-output table using the GTAP database. *Econ Syst Res* 23(2): 131–152.

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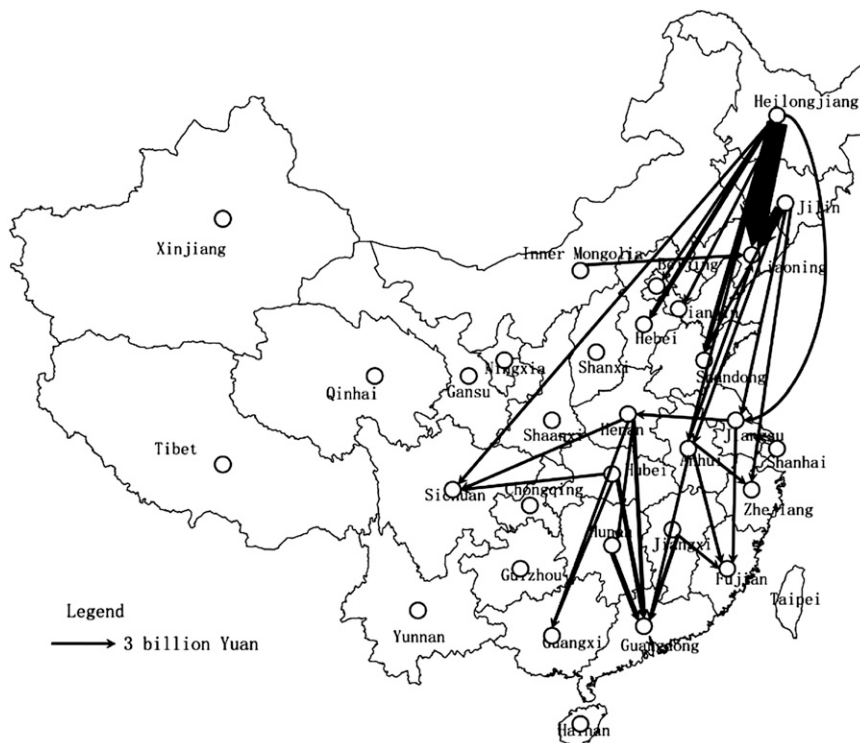


Fig. S1. Trade flows of the sample data in the agricultural sector.

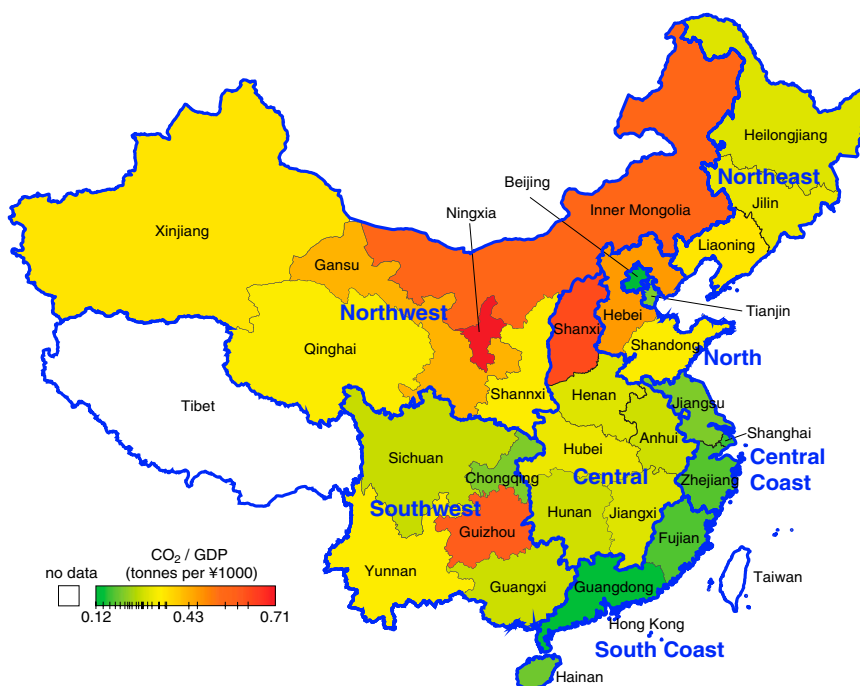


Fig. S2. Groupings of Chinese provinces and cities used in this study, and highlighting the carbon intensity [CO_2 per unit gross domestic product (GDP)] of each province/city.

Table S1. List of 30 modeled economic sectors

No.	Sector
1	Agriculture
2	Coal mining
3	Petroleum and gas
4	Metal mining
5	Nonmetal mining
6	Food processing and tobaccos
7	Textile
8	Clothing, leather, fur, etc.
9	Wood processing and furnishing
10	Paper making, printing, stationery, etc.
11	Petroleum refining, coking, etc.
12	Chemical industry
13	Nonmetal products
14	Metallurgy
15	Metal products
16	General and specialist machinery
17	Transport equipment
18	Electrical equipment
19	Electronic equipment
20	Instrument and meter
21	Other manufacturing
22	Electricity and hot water production and supply
23	Gas and water production and supply
24	Construction
25	Transport and storage
26	Wholesale and retailing
27	Hotel and restaurant
28	Leasing and commercial services
29	Scientific research
30	Other services

Table S2. Comparison between the estimations of the basic and augmented gravity models

Variables	Agriculture		Chemical		Electronics	
	Augmented	Basic GM	Augmented	Basic GM	Augmented	Basic GM
<i>t</i> test						
Constant	0.245	0.499	0.318	5.96	0.86	8.59
W_0Y	18.095		19.77		17.08	
W_dY	36.517		29.11		29.16	
W_wY	-10.808		-12.4		-11.87	
X_1	0.787	7.481	-0.25	-3.89	0.255	-0.908
X_2	0.604	4.545	1.69	8.19	3.617	8.16
X_3	-2.286	-5.123	-2.4	-10.26	-3.96	-12.98
R^2	0.719	0.113	0.678	0.192	0.665	0.232
<i>F</i> test	380.48	38.09	313.79	70.68	295.34	89.99

GM, gravity model.

Table S3. Top 15 origin–destination pairs of trade flows in the agricultural, chemical, and electronics sectors, trade flows in billion RMB

Rank	Agriculture	Chemical	Electronics
1	Hunan–Guangdong 20.6	Jiangsu–Zhejiang 37.0	Shanghai–Guangdong 98.8
2	Hebei–Shandong 19.0	Guangdong–Zhejiang 36.5	Jiangsu–Guangdong 97.0
3	Guangxi–Guangdong 17.3	Jiangsu–Guangdong 34.5	Fujian–Guangdong 35.0
4	Heilongjiang–Shandong 15.5	Guangdong–Guangxi 25.9	Guangdong–Shanghai 34.8
5	Hebei–Shanghai 14.8	Jilin–Heilongjiang 24.4	Guangdong–Jiangsu 34.3
6	Jilin–Shandong 11.3	Jilin–Liaoning 23.9	Tianjin–Guangdong 31.2
7	Hebei–Zhejiang 11.2	Shanghai–Zhejiang 22.7	Jiangsu–Beijing 22.8
8	Hebei–Jiangsu 10.1	Jiangsu–Henan 20.8	Guangdong–Zhejiang 21.8
9	Anhui–Shandong 9.4	Zhejiang–Shanghai 20.7	Jiangsu–Shanghai 19.9
10	Xinjiang–Shandong 9.1	Guangdong–Hunan 20.7	Jiangsu–Anhui 18.5
11	Hubei–Guangdong 8.7	Zhejiang–Guangdong 19.6	Jiangsu–Henan 16.9
12	Anhui–Shanghai 8.5	Jiangsu–Shanghai 19.5	Guangdong–Fujian 15.9
13	Jilin–Shanghai 8.5	Jiangsu–Shandong 18.2	Shanghai–Henan 15.4
14	Heilongjiang–Jilin 8.3	Zhejiang–Jiangsu 17.9	Shanghai–Beijing 14.1
15	Heilongjiang–Liaoning 8.2	Guangdong–Fujian 17.6	Guangdong–Henan 13.8

Table S4. Top 15 origin–destination pairs of trade flows in the agriculture sector under two alternative bandwidths, trade flows in billion RMB

Rank	Bandwidth = 1,000	Bandwidth = 500
1	Hunan–Guangdong 20.6	Hunan–Guangdong 33.1
2	Hebei–Shandong 19.0	Heilongjiang–Shandong 23.9
3	Guangxi–Guangdong 17.3	Hebei–Shanghai 19.0
4	Heilongjiang–Shandong 15.5	Hubei–Guangdong 16.8
5	Hebei–Shanghai 14.8	Jilin–Shandong 13.2
6	Jilin–Shandong 11.3	Hebei–Zhejiang 12.8
7	Hebei–Zhejiang 11.2	Guangxi–Guangdong 12.6
8	Hebei–Jiangsu 10.1	Sichuan–Shandong 11.5
9	Anhui–Shandong 9.4	Hebei–Jiangsu 11.4
10	Xinjiang–Shandong 9.1	Heilongjiang–Liaoning 11.3
11	Hubei–Guangdong 8.7	Jilin–Shanghai 10.7
12	Anhui–Shanghai 8.5	Anhui–Beijing 10.3
13	Jilin–Shanghai 8.5	Jilin–Jiangsu 10.3
14	Heilongjiang–Jilin 8.3	Hebei–Shandong 10.2
15	Heilongjiang–Liaoning 8.2	Anhui–Zhejiang 9.7