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The Belt, the Road, and the carbon emissions in China

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ABSTRACT

This paper explores the effect of the Belt and Road Initiative (BRI) on China's exports and the domestic carbon emissions induced by the exports. We employ a decomposition framework to assess the driving factors of the change of CO_2 emissions induced by China's exports to different destinations and evaluate the main contributions of the gap between the BRI countries and non-BRI (NBRI) countries. The decomposition results show that while the scale effect was the dominant force behind the pre-BRI emission growth, the contribution of the composition effect became more prominent after the inception of the Initiative. Our econometric analysis suggests that the Initiative leads to an increase in the share of carbon-intensive products in China's exports to the BRI countries by nearly 5 percentage points, which is approximately one quarter of the share of carbon-intensive exports to the BRI countries. A further investigation reveals that China's international project contracting is the main channel that has resulted in the increase of the share of carbon-intensive exports in China's exports to the BRI countries.

1. Introduction

Climate change and global warming are among the most challenging issues for all nations globally. The environmental consequences of increasing greenhouse gas emissions, particularly carbon dioxide (CO_2) emissions, are reflected not only in the rising temperatures of the planet but also consequently in all aspects of economic activities. As the world's largest CO_2 emitter, China accounts for nearly 30% of global emissions in 2018[1] and has attached great importance to carbon abatement with substantial efforts to curb carbon emissions (Liu et al., 2013). In 2015, China pledged to reduce its carbon intensity by 60–65% as part of its commitment to the Paris Agreement. More recently, China further promised to peak its carbon emissions by 2030 and to achieve carbon neutrality by 2060. Furthermore, all these specific carbon abatement targets are formally incorporated into China's 14th Five-Year Plan (2021–2025).

As the largest emerging economy, China has been actively seeking to expand its economic activities abroad to stimulate its economic growth. In 2013, China proposed the Belt and Road Initiative (BRI) which augments economic cooperation with the BRI countries by boosting international trade and foreign direct investment (FDI) activities, and hopes to reproduce the glory of the ancient Silk Road. As the Belt and Road Initiative continues to advance, China has strengthened cooperation with countries along the Belt and Road in all aspects. For example, China has opened the China-Europe Railway Express and constructed six economic corridors, which

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[1] The data is from the World Bank's World Development Indicators.

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are regarded as new land transport and international trade corridors for the BRI partners, thereby promoting further connectivity between Europe and Asia. As of June 2022, China-Europe Railway Express has reached 185 cities in 23 European countries.[2]

Both the construction of China-Europe Railway Express and six economic corridors involve a massive flow of goods and capital across international borders. From 2013 to 2021, China's exports to BRI countries increased significantly, and in 2020, China's exports in goods to BRI partners reached 786 billion dollars, representing 30% of China's total export volume.[3] And China's FDI flows to countries along the Belt and Road totaled 139.85 billion dollars from 2013 to 2020, involving 18 industry categories of nation economy. At the end of 2020, Chinese investors had set up >11 thousand overseas enterprises in the BRI countries.[4] In addition to the outward foreign direct investment (OFDI), China has also established the Silk Road Fund and the Asian Infrastructure Investment Bank to provide specialized financing services for infrastructure projects in BRI members, which further promotes the economic growth of the BRI countries and the partnership between BRI partners.

It's worth noting that 86% of the BRI countries are less developed countries[5] which are at earlier stages of economic development than China, and have demands for massive infrastructure and energy investments, making infrastructure connectivity a top priority in the Belt and Road Initiative. However, as the infrastructure-related projects and investments often come with high levels of pollution, a natural concern that comes with the BRI is whether the Initiative encourages high-carbon oriented demands and poses a potentially huge environmental cost to China's green development goals (Zhang, Liu, Zheng, & Xue, 2017).

In response to the concern above, we estimate China's carbon emissions induced by exports to the BRI countries and the non-BRI (NBRI) countries. As Fig. 1 reveals, China underwent significant growth in export-induced CO_2 emissions related to both BRI and NBRI countries from 2002 to 2007, followed by a transient decline during 2008 to 2009 because of the global financial crisis. However, when the world economy began to bounce back after 2009, the export-based CO_2 emissions related to the two destination groups showed a significant difference. The total CO_2 emissions related to the NBRI countries remained significantly below the pre-crisis level after 2009, while that of the BRI countries increased gradually and recovered to the pre-crisis level. Thus, what are the driving factors of the evolution of the China's exports induced CO_2 emissions to the BRI countries? And what are the main reasons causing the gap of CO_2 emissions between the BRI and NBRI countries?

To answer the above questions systematically, our research proceeds as follows. First, we start with a decomposition analysis to quantify the contributions of the major factors – technology, composition, and scale effects - influencing the CO_2 emissions of exports to the BRI and NBRI countries. We also discuss the gap of CO_2 emissions between the BRI countries and NBRI countries through a comparison after excluding the technology effects. Second, we conduct regression analyses to empirically check if the Belt and Road Initiative has led to a higher share of carbon-intensive exports to the BRI countries, for which systematic evidence is not yet available in the existing literature. We then analyze the mechanisms behind the change of exports, focusing on the role of China's international contracted projects and outward foreign direct investment. Finally, we conduct a host of additional checks to establish the validity and robustness of our main findings.

Our decomposition results show that although the scale effects were the main driver of the change of the CO_2 emissions in both BRI and NBRI countries for the years before the BRI was proposed, the impact of composition effects became more important after the initiative was proposed, especially for the BRI group (accounting for about one quarter of the change of CO_2 emissions). There is an average gap of 94 k tonnes in CO_2 emissions between the exports to the BRI and NBRI countries, the scale effect and the composition effect explain 81% and 19% of the difference respectively. Additionally, our regression results show that though there is no evidence that the Belt and Road Initiative has boosted China's exports to the BRI countries, after taking account for the endogeneity problem, the Initiative has led to an increase in the share of the exports of carbon-intensive products to the BRI countries by 5 percentage points, which is approximately one quarter of the share of carbon-intensive products in China's exports to the BRI countries. Moreover, we find that China's international contracted projects is the main channel which increase the share of China's carbon-intensive exports to the BRI countries, while China's outward foreign direct investment is not. Our basic findings withstand the parallel trend test, placebo test, and instrumental variable (IV) estimation.

Our research is connected to a large body of literature. Numerous studies have examined the economic effects of the Belt and Road Initiative, with the majority considering that trade and investment are its two primary economic objectives (Chen, 2016; Huang, 2016). The method of difference-in-differences (DID) estimation is widely used in studies on the effect of the Belt and Road Initiative on exports, and the conclusions vary depending on the selected control groups (Tian, Hu, Yin, Geng, & Bleischwitz, 2019; Wu, Chen, & Hu, 2021; Yu, Zhao, Niu, & Lu, 2020). These scholars regard the Belt and Road Initiative as a quasi-experiment, and usually estimate the impact of the Initiative on the volume of trade, while the direct impact on the structural change of the trade remains unclear. For example, Tian et al. (2019) find that the BRI policy have no significant effect on the volume of trade at the aggregate level, and the net growth of China's exports to the BRI countries was concentrated in pollution-intensive and resource-intensive industries. In their study, 58 BRI countries and 116 non-BRI countries are involved, and the method of DID is used. Different from Tian et al. (2019), Yu et al. (2020) only selects the world's top 30 trading countries as control group in their DID model, finding that China's export potential to the Belt and Road countries rose significantly after the initiative began, especially for exports of products in capital intensive industries. Other related studies include Huang (2016) and Ramasamy and Yeung (2019).

With respect to investment, the literature focuses on the influence of the Belt and Road Initiative on China's outward foreign direct

[2] The data is from the China's National Development and Reform Commission.

[3] The data is from *Statistical Communiqué of the People's Republic of China on the 2020 National Economic and Social Development*.

[4] The data is from *2020 Statistical Bulletin of China's Outward Foreign Direct Investment*.

[5] According to the classification of The World Economic Outlook (2018) published by IMF.

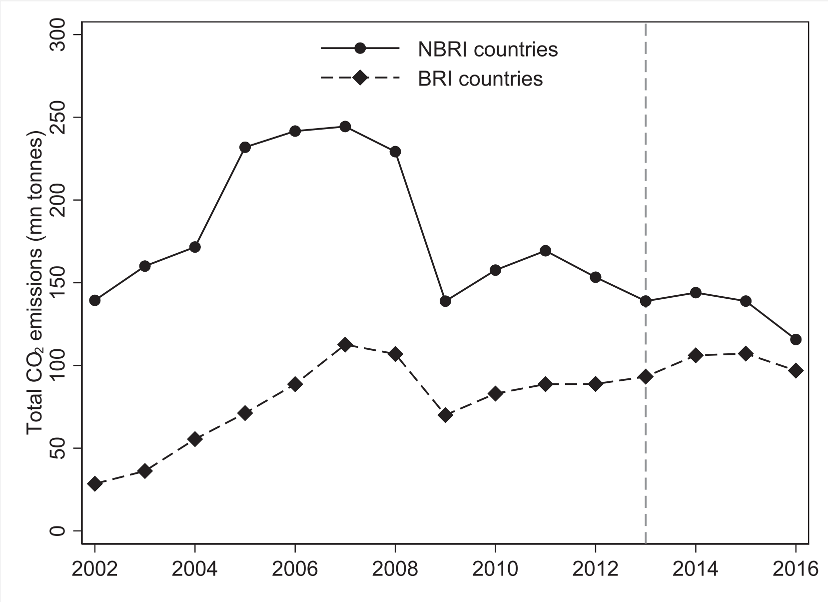

Fig. 1. China's CO_2 Emissions Induced by Exports to the BRI and NBRI Countries.
Note: The x-axis is for years. The y-axis is total CO_2 emissions. The solid line with dots represents the total CO_2 emissions related to the NBRI countries, and the dashed line with diamonds indicates the total CO_2 emissions related to the BRI countries. The vertical dashed line indicates the year before the policy was implemented. Source of data: authors' calculations based on the data from the China Emission Accounts and Datasets and the UN Comtrade Database.

investment (OFDI), with empirical analyses using different types of data (country-level data: Jiang, 2017; sector-level data: Nugent & Lu, 2021; firm-level data: Lyu, Lu, Wu, & Wang, 2019; Shao, 2020; Du & Zhang, 2018). The literature focuses on two types of OFDI—greenfield investment (Lyu et al., 2019) and mergers & acquisitions (M&A, Du & Zhang, 2018) activities. Most of them draw the conclusion that the BRI policy has increased China's OFDI flows to BRI countries by between 20% and 50%, depending on the selected econometric model, time periods and sampled countries. Contrary to most existing studies, Nugent and Lu (2021)'s study is based on country-sector-level data, and their result shows that the treatment effect of BRI policy on China's total FDI outflows is statistically insignificant or even negative.

With environmental issues receiving increased attention, the environmental effect of the Belt and Road Initiative also has been widely discussed. As trade connection is an important element of the Belt and Road Initiative, there is an important body of literature that focuses on the embodied carbon emissions of trade in Belt and Road countries, most of them are usually based on multi-regional input-output (MRIO) analysis (Lu et al., 2020). The MRIO method relies heavily on the input-output (I-O) tables, and the results are usually sensitive to the structure and precision of I-O tables. Among the frequently used worldwide I-O tables dataset, the Eora dataset provides the most complete I-O tables so far.[6] The Eora dataset provides a time series (1991–2015) of disaggregated I-O tables with environmental accounts for 190 countries, but there are a large number of missing values in year 2015. Due to the limitations with I-O tables, the existing studies using the MRIO method are often based on one single year's data (Cai, Che, Zhu, Zhao, & Xie, 2018; Han, Yao, Liu, & Dunford, 2018), or only focus on the BRI countries without any comparisons between the BRI countries and the others (Hu, Li, You, Liu, & Lee, 2020; Li, 2017; Muhammad, Long, Salman, & Dauda, 2020; Wang, Yang, Zhou, Liu, & Bi, 2022; Zhang & Jiang, 2020).

In addition to the aforementioned studies of the embodied carbon emissions of trade, some other scholars are concerned about the effect of changes in investment on carbon emissions in the context of the Belt and Road Initiative. These studies focus on green infrastructure investment (Yang & Yang, 2019), renewable energy investment (Gu & Zhou, 2020), and Chinese OFDI in the energy sector (Liu, Wang, Jiang, & Wu, 2020), concluding that the increase in green investment in the context of the Belt and Road has decreased the carbon emissions of the host country. With a few exceptions, Khan and Bin (2020) find that foreign direct investment led to the increase in carbon emissions based on panel data of 65 countries from 1985 to 2017. Owing to the different types of investment, the changes in investment under the Belt and Road and its impact on the climate and environment need to be further examined.

In summary, most studies focus on the effect of BRI on exports, despite the heterogeneous across sectors are mentioned, there is rare research directly discuss the structural change of exports caused by the BRI policy. Moreover, these studies usually regard the proposal of the Belt and Road Initiative as a quasi-experiment, omitting the obvious selection bias of the BRI countries (Nugent & Lu, 2021; Shao, 2020; Tian et al., 2019; Wu et al., 2021; Yu et al., 2020). This becomes a concern as it is highly unlikely that the formation of the

[6] Existing worldwide I-O tables datasets are listed in the Appendix (see Table A1).

BRI partnership was random. In fact, the Chinese government may have selected the BRI countries based on its political and economic agenda. Without addressing this potential threat to the estimation, the usual DID estimates are likely to be biased. Jiang, Ma, and Wang (2021) is a rare study that considers the above endogeneity problem by combing the DID model with the propensity score matching (PSM) method. However, the PSM method only can eliminate the bias induced by observable factors, while that induced by unobservable factors still remain untouched. In this study, we attempt to deal with the endogeneity problem by introducing a novel instrument variable estimation.

Meanwhile, with respect to the environmental effect of the BRI policy, due to method and data limitations, the gap in carbon missions between BRI and non-BRI countries is rarely discussed, which deserves further discussion. Additionally, most of the existing studies have focused on the environmental impact of the BRI policy on the BRI countries other than China (Ascensão et al., 2018; Gu & Zhou, 2020; Hughes, 2019; Jiang et al., 2021; Lechner, Chan, & Campos-Arceiz, 2018; Liu et al., 2020; Tracy, Shvarts, Simonov, & Babenko, 2017; Wu et al., 2021). Surprisingly, very limited research has discussed the environmental impact of the Initiative on China itself. As the initiator and the largest exporter to the BRI countries, China's exports will, to a great extent, not only affect the environment of the BRI partners but also the environmental quality of China itself. One particular mechanism of the Initiative extends China's supply chain by expanding exports to the BRI countries which leads to the growth of China's energy-intensive industries (such as mining, iron, and steel), in turn, accelerating energy combustion and consequently increasing total global carbon emissions (Zhang et al., 2017).

Our research contributes to the existing literature in several aspects. First, we focus on the economic and environmental impact of the Initiative on China itself. Specifically, we not only assess the impact of the Belt and Road Initiative on the scale of exports, but also emphasize its impact on the structure of China's exports from the climate change perspective. In addition, we analyze the mechanisms (CIPC and OFDI) behind the policy effect of the BRI on China's export structure, offering new findings to the literature.

Second, we estimate the CO_2 emissions induced by China's exports to the BRI countries and NBRI countries for the extended period between 2009 and 2016. Unlike the studies based on MRIO analysis, this study uses the logarithmic mean Divisia index model to decompose the change of CO_2 emissions into three effects, and quantify the contributions of each factor in two periods (before and after the Belt and Road Initiative) separately. Moreover, the sources of the gap between the two groups are discussed.

Third, we propose a novel instrumental variable to deal with the endogeneity problem. Specifically, we construct a dummy variable based on whether a country had any trade post along the historical ancient Silk Road routes to instrument the current BRI partner status. The rationale for this strategy is based on the notion that the instrument is correlated with the BRI membership but is also largely different from the latter and is pre-determined by a host of historical factors that are no longer relevant today. Thus, this strategy to some extent mitigates the selection concern.

The rest of the paper is structured as follows. Section 2 presents the framework of the decomposition analysis, the data sources, and the decomposition results. Section 3 conducts the empirical analysis using econometric methods. Section 4 concludes and provides policy implications.

2. Decomposition analysis

2.1. Decomposition framework

Decomposition analysis aims to disentangle an aggregate change in a variable into multiple contributing factors. In the context of research in carbon emissions, the commonly used methods include production-theoretical decomposition analysis (PDA), structural decomposition analysis (SDA) and index decomposition analysis (IDA).

The PDA methods emphasizes the technology factors related to CO_2 emission changes from the productive efficiency perspective. It applies distance functions and decomposes the technology factor by solving a system of linear programming equations (Fan et al., 2019; Zhou & Ang, 2008). The SDA methods achieve additive decomposition based on the Input-Output tables, allowing it to reflect the production technology and demand-side effects as well as trade-related issues by simple algebraic operations. However, the application of the SDA methods is constrained by its demanding requirements for the completeness of information from Input-Output tables. Compared to the SDA methods, the IDA methods can be used to implement not only additive decomposition but also multiplicative decomposition by rather straightforward calculations. In addition, the IDA methods have been increasingly used in economy-wide energy and emissions studies owing to the easy accessibility of the data at the country level.

Among the various IDA methods,[7] the logarithmic mean Divisia index (LMDI) model is regarded as the most preferred method due to its many outstanding advantages, such as completeness of decomposition, adaptability to data sets, and result interpretation (Ang, 2004; Mousavi, Lopez, Biona, Chiu, & Blesl, 2017; Xu & Ang, 2013).[8] Therefore, in this research we use the LMDI model for the additive decomposition and analysis of the change in CO_2 emissions. To be specific, CO_2 emissions of China are calculated as the product of three factors, as in the following equation:

$$CE_t^d = \sum_j CE_{jt}^d = \sum_j CI_{jt}^d \times \frac{Exp_{jt}^d}{Exp_t^d} \times Exp_t^d \tag{1}$$

[7] IDA methods are mainly divided into Laspeyres, Shapley/Sun, logarithmic mean Divisia index (LMDI), and other Divisia methods.

[8] Decomposition without a residual term is called complete decomposition. It is also known as exact or perfect decomposition; LMDI is adaptable to the cases with zero values, which is inevitable in some data sets; The base and final years may be reversed in a LMDI model.

where subscript d denotes BRI partner country, and subscripts j and t indicate industry and time respectively; CE_{jt}^{d} is the CO_2 emission of industry j in year t, and CE_{t}^{d} is the CO_2 emissions of all industries in China as a result of exports to country d; CI_{jt}^{d} is CO_2 emission intensity of industry j, reflecting the technological level; Exp_{jt}^{d} is the exports of industry j, Exp_{t}^{d} is the total exports of all industries to d, and $\frac{Exp_{jt}^{d}}{Exp_{t}^{d}}$ is the share of exports for industry j. To simplify the notations, we use T_{jt}, C_{jt} and S_t to represent CI_{jt}^{d}, $\frac{Exp_{jt}^{d}}{Exp_{t}^{d}}$ and Exp_{t}^{d} as follows:

$$CE_t = \sum_j CE_{jt} = \sum_j T_{jt} C_{jt} S_t \tag{2}$$

The LMDI model uses the logarithmic mean which does not produce residuals and is thus easier to calculate even with many components. The logarithmic form can be expressed as in Eq. (3):

$$L(a,b) = \begin{cases} \dfrac{a-b}{lna - lnb} & , \quad a \neq b \\ a & , \quad a = b \end{cases} \tag{3}$$

According to Eq. (3), the change in the total carbon emissions of industry j is measured by

$$\Delta CE_j \equiv CE_{jt} - CE_{jt-1} = L(CE_{jt}, CE_{jt-1}) \times ln\left(\frac{CE_{jt}}{CE_{jt-1}}\right) \tag{4}$$

Since $CE_{jt} = T_{jt}C_{jt}S_t$, we can further decompose the change in CO_2 emissions as follows:

$$\begin{aligned} \Delta CE_j &= L(CE_{jt}, CE_{jt-1}) \times ln\left(\frac{T_{jt}}{T_{jt-1}} \times \frac{C_{jt}}{C_{jt-1}} \times \frac{S_t}{S_{t-1}}\right) = L(CE_{jt}, CE_{jt-1}) \times \left[ln\left(\frac{T_{jt}}{T_{jt-1}}\right) + ln\left(\frac{C_{jt}}{C_{jt-1}}\right) + ln\left(\frac{S_t}{S_{t-1}}\right)\right] \\ &= L(CE_{jt}, CE_{jt-1}) \times \left[\frac{T_{jt} - T_{jt-1}}{L(T_{jt}, T_{jt-1})} + \frac{C_{jt} - C_{jt-1}}{L(C_{jt}, C_{jt-1})} + \frac{S_t - S_{t-1}}{L(S_t, S_{t-1})}\right] = \frac{L(CE_{jt}, CE_{jt-1})}{L(T_{jt}, T_{jt-1})}\Delta T_j + \frac{L(CE_{jt}, CE_{jt-1})}{L(C_{jt}, C_{jt-1})}\Delta C_j + \frac{L(CE_{jt}, CE_{jt-1})}{L(S_t, S_{t-1})}\Delta S \end{aligned} \tag{5}$$

We define

$$g_j(\Delta T) \equiv \frac{L(CE_{jt}, CE_{jt-1})}{L(T_{jt}, T_{jt-1})}\Delta T_j \tag{6}$$

$$g_j(\Delta C) \equiv \frac{L(CE_{jt}, CE_{jt-1})}{L(C_{jt}, C_{jt-1})}\Delta C_j \tag{7}$$

$$g(\Delta S) \equiv \frac{L(CE_{jt}, CE_{jt-1})}{L(S_t, S_{t-1})}\Delta S \tag{8}$$

Therefore, the change in CO_2 emissions of industry j for country d, ΔCE_j, can be decomposed into three effects: the technology effect $g_j(\Delta T)$, the composition effect $g_j(\Delta C)$, and the scale effect $g(\Delta S)$.

$$\Delta CE_{jt} \equiv CE_{jt} - CE_{jt-1} = g_j(\Delta T) + g_j(\Delta C) + g(\Delta S) \tag{9}$$

The total effect of the BRI countries for all the industries can then be aggregated based on Eq. (9) as follows:

$$\Delta CE_t^{BRI} = \sum_{d \in BRI}\sum_j \Delta CE_{jt}^{d} = \sum_{d \in BRI}\sum_j g_j^d(\Delta T) + \sum_{d \in BRI}\sum_j g_j^d(\Delta C) + \sum_{d \in BRI}\sum_j g^d(\Delta S) \tag{10}$$

where $\sum_{d \in BRI}\sum_j g_j^d(\Delta T)$, $\sum_{d \in BRI}\sum_j g_j^d(\Delta C)$ and $\sum_{d \in BRI}\sum_j g^d(\Delta S)$ are the aggregated technology effect, the composition effect, and the scale effect for all the industries of the BRI countries, respectively. A negative technology effect, i.e. $\sum_{d \in BRI}\sum_j g_j^d(\Delta T) < 0$, implies a decrease in the CO_2 emission intensity as a result of technology improvement. In this study, we assume the technologies are identical between production activities for domestic and for foreign markets.[9] A negative composition effect, i.e. $\sum_{d \in BRI}\sum_j g_j^d(\Delta C) < 0$, implies a change in the industrial structure which has led to a drop in CO_2 emissions; in other words, the industrial structure has become cleaner (with a low overall carbon intensity). Similarly, a negative scale effect, i.e. $\sum_{d \in BRI}\sum_j g^d(\Delta S) < 0$, implies a decrease in the scale of exports which has led to less CO_2 emissions.

[9] Even though the difference in the technology effect between the NBRI and BRI group still exits due to the fact that the total CO_2 emissions in two groups are different, $L(CE_{jt}, CE_{jt-1})$ and $g_j(\Delta T)$ are different according to the Eq. (6). Essentially, in addition to the direct effect, the technology will affect the other effects and further has indirect impact on the total change of CO_2 emissions.

2.2. Data

This study uses a panel dataset of China's industrial exports from 2009 to 2016 for the decomposition analysis. China's export data that is specific for its trade partners and products is extracted from the UN Comtrade Database. The data for analysis includes 61 countries along the route of the Belt and Road Initiative (BRI countries) and 128 Non-BRI countries. The names of the BRI countries are listed in Table 1, which is obtained from the official definition of China.[10]

Since the industry classification system of China is different from that of the Harmonized Commodity Description and Coding System (HS), we match the two as follows. First, we convert the 8-digit HS classification to the 2-digit China Industry Classification System (CIC)[11] using the corresponding table provided by Brandt, Biesebroeck, Wang, and Zhang (2019). Second, the missing values that are not matched in the first step are supplemented by the corresponding table from Upward, Wang, and Zheng (2013). Third, for a few HS codes that cannot be mapped to a unique 2-digit CIC code, we assign the closest CIC code for each of them manually by mapping the names of the commodities. Finally, we derive a dataset of 35 manufacturing industries (out of 45 industries) for which CO_2 emissions data are available. It is worth noting that the Chinese government updated the CIC table in 2011 during our sample period and there are several small adjustments in industry classifications between the 2002 and 2011 versions of the CIC system. To make the classification time consistent, we merge the industries[12] that experienced changes in their classification into broader sectors. We end up having a panel dataset including 32 industries which account for at least 99% of Chinese exports each year.

The CO_2 emissions data is acquired from the China Emission Accounts and Datasets which provide the most accurate and up-to-date energy, emission and socioeconomic accounting inventories for China (Shan et al., 2018). Most of the previous studies used the value-added data derived from the Annual China Industry Economy Statistical Yearbook (ACIESY) to estimate the CO_2 emission intensity for each sector (Ma et al., 2019; Zhang et al., 2019). However, as the value-added data are not reported in the yearbooks after 2007, the later years' data are imputed based on the published annual average growth rate of the value-added (He, 2015; Lin & Liu, 2015; Wang, Ma, & Cao, 2019). To check the accuracy of this approach, we compared the actual value-added data and the imputed values for the years before 2007. Unfortunately, a significant discrepancy is found between the two data series. Thus, we use the industrial output data (2002–2016) to calculate the CO_2 intensity instead, which is also collected from ACIESY. The CO_2 emission intensity is defined as the CO_2 emissions produced per monetary unit (tonnes per 10,000 Yuan) of output. The exchange rates are obtained from the website of the National Bureau of Statistics of China (NBSC). All values in this analysis are deflated into 2002 constant price using the industrial producer price indexes also from the website of NBSC.

2.3. Decomposition results

To quantify the relative contributions of the major factors influencing the evolution of CO_2 emissions, this study uses a LMDI model to conduct the decomposition analysis. To better understand the effect of the Belt and Rode Initiative, we divide the countries into two groups, i.e. BRI group and NBRI group. To rule out the confounding effects of the global financial crisis, we select the period of 2009 to 2016 for the decomposition. We further divide the time span into two periods according to the occurrence of the BRI: 2009–2012 and 2013–2016.[13]

Before the decomposition analysis, it is helpful to throw a glance at how carbon intensity (CI), the total value of exports, and the industrial structure evolved from 2009 to 2016. First, Fig. 2 compares CO_2 intensities in 2009 and 2016 for all industries.[14] It is seen that the industry of *Production and Supply of Electric Power, Steam and Hot Water* has the highest CO_2 intensity, which is not surprising since 77% of China's power stations are fueled by coal[15] while coal burning is the main source of CO_2 emissions in the country. Next in the ranking are the industries of *Nonmetal Mineral Products*, *Smelting and Pressing of Ferrous Metals*, *Coal Mining and Dressing*, *Petroleum Processing,* and *Coking*. The industry of *Electronic and Telecommunications Equipment*, *Tobacco Processing*, *Electric Equipment and Machinery*, *Transportation Equipment*, *Furniture Manufacturing* are relatively clean (i.e. with low CO_2 intensities). We also observe that the CO_2 emission intensities of most industries decreased by 20% from 2009 to 2016, among which, the industry of *Electric Equipment and Machinery* has the sharpest drop with a reduction of 63%.

Second, we compare the trends and shares of exports from China to the BRI and NBRI countries. Fig. 3 shows that the trends of the exports from China to the two groups were similar. Specifically, the export scales to both the BRI and NBRI countries show a persistent increase from 2009 to 2013, then remain stable for the rest of the period. Meanwhile, the share of the exports to the BRI countries has

[10] The website of the BRI definition is https://www.yidaiyilu.gov.cn

[11] Industrial Classification for National Economic Activities in 2002 (GB/T 4754–2002).

[12] The sector Timber Processing, Bamboo, Cane and the sector Palm Fiber and Straw Products are merged into the sector Timber Processing, Bamboo, Cane and the sector Palm Fiber & Straw Products. The sector Cultural, Educational and Sports Articles and the sector Other Manufacturing Industry are merged into the sector Cultural, Educational and Sports Articles & Other Manufacturing Industry; The sector Ordinary Machinery and the sector Instruments, Meters, Cultural and Office Machinery are merged into the sector Ordinary Machinery & Instruments, Meters, Cultural and Office Machinery.

[13] We used the data from 2009 to 2012 in order to calculate the total change of 2010, 2011 and 2012, which are three years before the BRI. Likewise, the data from 2013 to 2016 was applied to acquire the total change of 2014, 2015 and 2016, which are three years after the BRI.

[14] We assume the production technologies for export products to different destinations are identical. It is reasonable since all the products are produced in China no matter the export destinations were the NBRI group or the BRI group.

[15] We derived the average proportion of thermal power generation from 2009 to 2016 based the data from NBSC.

Table 1
The List of the Belt and Road countries.

Geographic Region	Members	Numbers
Northeast Asia	Mongolia ; Russian Federation	2
Southeast Asia	Singapore ; Indonesia ; Malaysia ; Thailand ; Viet Nam ; Philippines ; Cambodia ; Myanmar ; Lao People's Dem. Rep. ; Brunei Darussalam ; Timor-Leste	11
South Asia	India ; Pakistan ; Sri Lanka ; Bangladesh ; Nepal ; Maldives ; Bhutan	7
West Asia North Africa	United Arab Emirates ; Kuwait ; Turkey ; Qatar ; Oman ; Lebanon ; Saudi Arabia ; Bahrain ; Israel ; Yemen ; Egypt ; Iran ; Jordan ; **Syria** ; Iraq ; Afghanistan ; State of Palestine ; Azerbaijan ; Georgia ; Armenia	20
Central and Eastern Europe	Poland ; Albania ; Estonia ; Lithuania ; Slovenia ; Bulgaria ; Czechia ; Hungary ; North Macedonia ; **Serbia** ; Romania ; Slovakia ; Croatia ; Latvia ; Bosnia Herzegovina; **Montenegro** ; Ukraine ; Belarus ; Rep. of Moldova	19
Central Asia	Kazakhstan ; Kyrgyzstan ; Turkmenistan ; Tajikistan ; Uzbekistan	5

Note: This table lists the names of BRI countries by region. Syria, Serbia and Montenegro are not included due to the lack of data. Source of data: the official website of BRI (https://yidaiyilu.gov.cn).

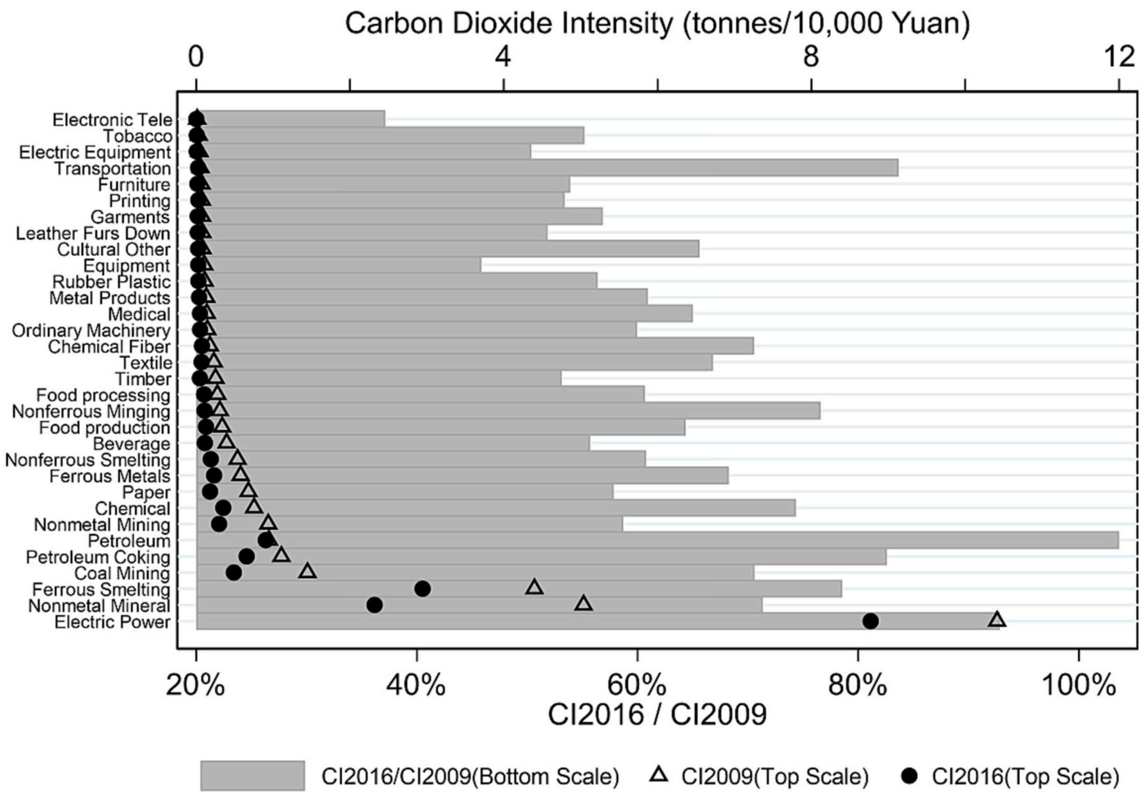

Fig. 2. Comparison of CO_2 Intensities in 2009 and 2016.
Note: This figure compares CO_2 intensities in 2009 and 2016 for all industries. The top x-axis represents CO_2 intensity (CI) as CO_2 emission per output, the bottom x-axis is CI in 2016 (CI2016) divided by CI in 2009 (CI2016). The y-axis is for industries, which is in ascending order of CO_2 intensities in 2009. The hollow triangles are CIs in 2009, and the solid dots represent CIs in 2016. The bars are CIs in 2016 divided by CIs in 2009 for all industries. Source of data: The CO_2 emissions data is from the China Emission Accounts and Datasets and the output data is from the Annual China Industry Economy Statistical Yearbook.

increased quickly and persistently, especially for 2013–2014, which suggests that the relative importance of the trade with the BRI countries has been increasing during the sample period.

Third, we explore the structural change of China's exports to the BRI and NBRI countries. Table 2 reports the top 5 industries with the greatest export share increase for the BRI and NBRI country group separately. From the table, we find that the trade with the BRI group appears to be more polluting after 2013 since the number of polluting industries has increased from 1 to 3. For the NBRI countries, though the number of polluting industries remains unchanged, the rank of the polluting industry has increased from the fourth to the second.

We then focus on the aggregated CO_2 emission changes. The effects of all the components of the emission changes of the NBRI and BRI groups in the two periods are illustrated by the stacked bars in Fig. 4. By comparing the effects above zero and below zero, we can easily derive that the total effects were positive in both groups during 2009 to 2012, and the total effect in the NBRI became negative

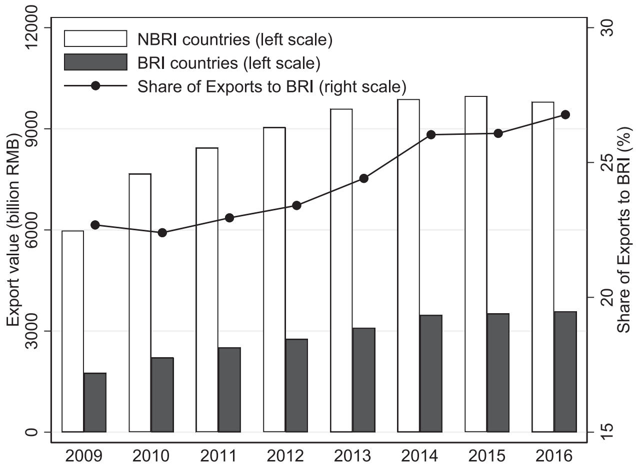

Fig. 3. Export Values to the BRI and NBRI Group (2009–2016).
Note: The x-axis is for years. The left y-axis represents export value, and the right y-axis is the share of China's exports to BRI countries. The solid line with dots shows the share of China's exports to BRI countries. The hollow bars are China's exports to the NBRI countries, and the solid bars represent China's exports to the BRI countries. Source of data: UN Comtrade Database.

Table 2
Top 5 Industries with Greatest Increase in Export Share.

Time interval	Rank	NBRI		BRI	
		Industry	Polluting	Industry	Polluting
	1	Electronic Tele	0	Transportation	0
	2	Metal products	0	**Ferrous Smelting**	**1**
2009–2012	3	Ordinary machinery	0	Rubber Plastic	0
	4	**Ferrous Smelting**	**1**	Furniture	0
	5	Cultural Other	0	Ordinary machinery	0
	1	Electric Equipment	0	Electronic Tele	0
	2	**Chemical**	**1**	**Ferrous(smelting/pressing)**	**1**
2013–2016	3	Transportation	0	Electric equipment	0
	4	Garments	0	**Chemical**	**1**
	5	Rubber Plastic	0	**Petroleum Coking**	**1**

Note: This table displays the numbers of polluting industries in the top 5 increasing industries in the NBRI and BRI groups across the two periods. The columns of Industry show the top 5 industries with greatest increase in export share during the corresponding periods. Polluting is a dummy variable which equals one if the CO_2 intensity is larger than the median, and zero otherwise. Source of data: authors' calculations based on the data from the Annual China Industry Economy Statistical Yearbook, the China Emission Accounts and Datasets, and the UN Comtrade Database.

during 2013 to 2016 while that in the BRI group remained slightly positive, which demonstrates that CO_2 emissions in the NBRI group increased during 2009 to 2012 but decreased during 2013 to 2016, while CO_2 emissions in the BRI group appeared to experience a continuous rise during the two periods although the speed of increase slowed down. Notably, scale effects were the primary contributing factor to the change in the CO_2 emissions in both groups during 2009 to 2012, resulting in 59 and 36 million tonnes of CO_2 emissions increase for the NBRI group and BRI group, respectively. Nevertheless, for the period of 2013 to 2016 the scale effect plummeted while the technology effect took over as the main driving force for both groups. By contrast, for both groups the composition effect had little impact on the change in the CO_2 emissions during the first period, although it gained its weight during 2013 to 2016, especially for the BRI group, accounting for about one quarter of the change of CO_2 emissions. The technology effect decreased during the second period for both groups, implying a slow-down in the technological progress of carbon emissions.

The decomposition results reported in Fig. 4 only show the contributions of the three effects for the two groups on the basis of aggregated decompositions. It is also worth investigating the average decomposition results since the number of countries for the two groups are different, i.e. there are 128 countries in the NBRI group while there are only 61 countries in the BRI group. Note that we have already assumed that the production technologies are identical for all export destinations, thus by definition, the BRI policy will have no effect on the technology gap between the two groups and the technology effects should be omitted.

The average scale and composition effects are presented in Table 3. On the one hand, the average scale effects declined considerably from the first to the second period, i.e. with an average 360 k tonnes decline in the BRI countries, and a greater decline of 437 k tonnes in the NBRI group, which are consistent with the results reported in Fig. 4. On the other hand, Table 3 reveals that the structural change has caused an average increase of 48 k tonnes of CO_2 emissions for each BRI country, which is consistent with our findings that the industrial structure change of the BRI group probably became more polluting in Table 2. Meanwhile, the composition effect also saw a

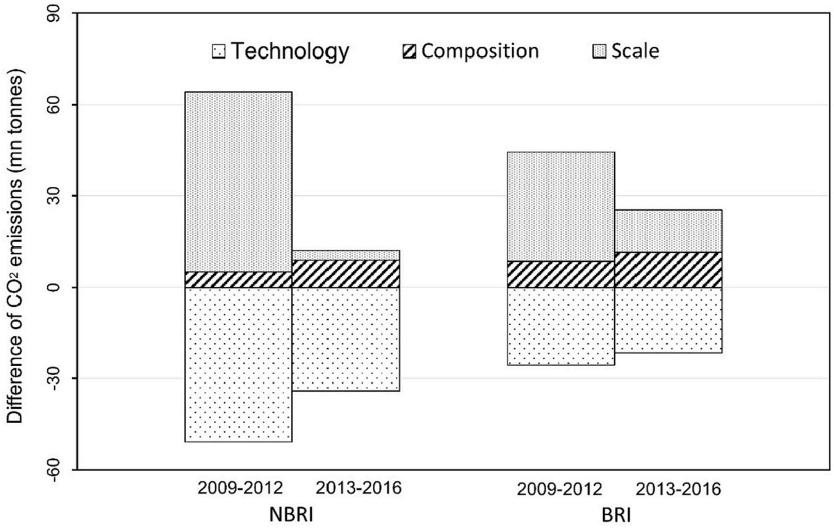

Fig. 4. Factors Contributing to CO_2 Emission Changes in China's Exports.
Note: This figure shows the contributions of the three effects to CO_2 emission changes: the technology effect, the composition effect, and the scale effect. The x-axis indicates the two periods for the two country groups. The y-axis is the difference of CO_2 emissions. If the y-value is below zero, it means the effect reduces the CO_2 emissions, and vice versa. A negative technology effect implies a decrease in the CO_2 emission intensity as a result of technological improvement. A negative composition effect implies a change in the industrial structure which leads to a drop in CO_2 emissions. A positive scale effect implies an increase in the scale of exports which leads to less CO_2 emissions. Source of data: authors' calculations based on the data from the Annual China Industry Economy Statistical Yearbook, the China Emission Accounts and Datasets, and the UN Comtrade Database.

Table 3
Decomposition Results of the Individuals in Two Groups (Unit: kilo tonnes).

Groups	Indicators	Period	Scale Effect	Comp Effect	Scale + Comp Effects
	CO_2 change	2009–2012	584.98	142.45	727.43
BRI	CO_2 change	2013–2016	224.68	190.64	415.32
	ΔCO_2_BRI		**−360.3**	**48.19**	−312.11
	CO_2 change	2009–2012	461.75	39.88	501.64
NBRI	CO_2 change	2013–2016	24.68	70.50	95.18
	ΔCO_2_NBRI		**−437.07**	**30.62**	−406.46
ΔCO_2_BRI - ΔCO_2_NBRI			**94.35**	**76.77**	**17.57**
Contribution rate			**100.00%**	**81.37%**	**18.62%**

Note: ΔCO_2_BRI indicates the average difference between the CO_2 changes in China's exports to a BRI country in 2013–2016 and 2009–2012; ΔCO_2_NBRI has the same meaning as above except that it is for a NBRI country. The row of Contribution rate indicates the share of each effect. Source of data: authors' calculations based on the data from the Annual China Industry Economy Statistical Yearbook, the China Emission Accounts and Datasets, and the UN Comtrade Database.

mild increase by 31 k tonnes of CO_2 emissions on average in the NBRI group. As a result, the scale and composition effect together induced a 312-thousand tonnes decrease in the average CO_2 emissions for the BRI countries from the first to the second period, while that for the NBRI countries is 406 k tonnes. The gap of the scale and composition effect between the BRI and NBRI groups is about 94 k tonnes. Moreover, scale effect explains 81% of the gap while composition effect accounts for 19%.

3. Econometric analysis

3.1. Model specification and data

Decomposition analysis gives us the first picture of the contributions of the main factors and the sources of the gap of the CO_2 emissions between two group, the BRI group and the NBR group. However, the analysis only shows the average result of the two groups, ignoring the heterogeneity across countries in each group. In this section, we attempt to use econometric analysis, which allows us to control the heterogeneity of countries and other factors, to further explore the casual relationship between the BRI policy and the change in export scale and structure (share of carbon-intensive products) of China. Specifically, we refer to the work of Lyu et al. (2019) and Jiang et al. (2021) and construct the following regression models:

$$lnExports_{dt} = \alpha + \beta BRI_d \times Post_t + X_{dt}\Gamma + \theta_d + T_t + \varepsilon_{dt} \tag{11}$$

$$SharePol_{dt} = \alpha + \beta BRI_d \times Post_t + X_{dt}\Gamma + \theta_d \quad (12)$$

where the dependent variable $lnExports_{dt}$ is the log value of China's exports to partner d in year t, and $SharePol_{dt}$ is the share of polluting industries in China's exports to d in year t, a broad measure of the pollution intensity of China's exports at the partner-year level. An industry is classified as a polluting industry if the average CO_2 emission intensity (average over time) of this industry is higher than the median of the average intensities of all industries. BRI_d is a dummy indicator for a BRI country as defined in Table 1. $Post_t$ is a time dummy which equals one for the years after 2013 (BRI was proposed in September 2013, thus we take 2014 as the first year that the BRI policy was put in place) and zero for the years before 2014; X_{dt} is a vector of country-year-specific controls including economic size (*GDP*), population (*Pop*), urban development (represented by the share of urban population in total population, *Urb*), and distance between the partner and China. We take the logarithm forms of the GDP and population as *lnGDP*, *lnPop* to reduce the effects of outliers and heteroscedasticity, and multiply the distance by the year dummies to allow the effect of distance to vary over time. θ_d and T_t represent destination and year fixed effects, respectively, which are included to remove the influence from confounding factors at the respective levels.

The specification in Eqs. (11) or (12) follows a difference-in-difference (DID) strategy. The first difference estimates the pre-BRI difference between the BRI and NBRI country group, and the second further estimates how the above difference changes post BRI. The first difference would have been captured by the coefficient of the dummy BRI_d, but is absorbed by the country fixed effects θ_d. The key parameter of interest is β, the coefficient of the interaction term between BRI_d and $Post_t$, which is the DID estimator capturing the effect that the Belt and Road Initiative has had on China's exports to its partners and the share of polluting industries in total exports, estimated as the difference between the observed post-BRI data and the counterfactual scenario of what would have happened without the BRI policy. Data on GDP, population, and urbanization of trade partners is collected from the World Bank's World Development Indicators, and the distances between China and other countries are from CEPII Gravity database. As before, all monetary values are converted to 2002 prices. The summary statistics of the key variables are presented in Table 4.

3.2. Results and discussions

The estimation results of Eqs. (11) and (12) are reported in Table 5. Columns (1)–(2) display the effect of the BRI policy on China's total exports (export scale). With all fixed effects included, the coefficients of the interaction term *BRI×Post* are both positive and statistically significant even at the 10% level, suggesting that there is no evidence that the Belt and Road Initiative has boosted China's exports scale to the BRI countries. And the observed exports gap in Fig. 3 between the BRI and NBRI groups may be driven by country-specific or year-specific effects rather than the BRI policy itself. The results are consistent with that of Tian et al. (2019). In their study, they find that the trade scale of China (measured by total exports, total imports, and net exports) with the BRI countries does not differ from that with the NBRI countries at the aggregate level.

Columns (3)–(4) report the effect of the BRI policy on the pollution intensity of China's exports, measured by the share of China's polluting industries' exports in total exports to its partners. Without any controls, we only induce the country and year fixed effects and cluster the standard errors at the country level in Column (3). The coefficient of interaction term in Column (3) is positive and statistically significant at the 10% level. We further add a set of controls in Column (4), the size of the coefficient has a slight increase and it becomes more significant at the 5% level. Therefore, we conclude that the Belt and Road Initiative has led to a 2 percentage points increase in the pollution intensity of China's exports to the BRI countries, which is approximately one-tenth of the average share to the BRI countries.[16]

The above results show that the Belt and Road Initiative has no significant impact on the total export volume, but it does make the export structure of China to the BRI countries more carbon-intensive, which means that the exports that are not carbon-intensive are crowded out. In fact, the Belt and Road Initiative, with its emphasis on policy alignment, connectivity of infrastructure networks, reducing trade frictions, financial integration and people-to-people contact, was proposed by the Chinese government with strong geopolitical as well as economic motivations. Economic development, therefore, is not the whole purpose of the Belt and Road Initiative, and economic activity under special subsidies granted by the policy is not always market-driven.

More commonly, Chinese state-owned conglomerates (e.g. China Railway and China Electric Construction) have taken the lead in responding to the government's call, under some exclusive subsidies, for strengthening cooperation with these BRI countries on large infrastructure projects. For example, by building six economic corridors, signing cooperation agreements for port, rail and highway projects, these major infrastructure projects often involve a high demand for carbon-intensive intermediate or final products which are often imported from China. This drives the product mix of China's exports to these countries towards the more polluting end.

Considering the fact that nearly 90% of the Belt and Road countries are less developed countries with low per capita income, relatively small market size, and limited foreign reserve, the crowding-out effects are more likely to be at play in these destinations than others. With limited purchasing power, when these BRI countries import carbon-intensive infrastructure-related products from China, their demand for cleaner products from China could be rather squeezed. This would be more of the case when these carbon-intensive imports are funded by debts.

It's also worth noting that if China imports more low-carbon products from the BRI countries instead of carbon-intensive products, then the imports from the BRI countries will actually help to offset the increase in export-induced carbon emissions. To explore the

[16] The average share of the polluting industries in total exports to the BRI countries is about 20%.

Table 4
Descriptive Statistics of All the Key Variables.

Symbol	Variables Description	Count	Mean	SD	Min	Max
Exports	China's exports to the partner (million US$)	1512	9612.57	36,550.95	0.06	410,539.53
SharePol	Export share of polluting industries (%)	1512	18.95	9.64	0.03	87.62
GDP	GDP (million US$)	1512	244,711.41	1,114,332.53	22.81	14,347,904
Pop	Population (10,000 persons)	1512	2963.12	10,068.13	1.04	132,450.95
Urb	Urban population of total population (%)	1512	58.20	23.55	10.38	100.00
Dist	Distance between the partner and China (Kilometers)	1512	9079.14	3828.16	955.65	19,297.47

Note: This table reports the descriptive statistics of key variables. Source of data: export data is from UN Comtrade Database; export share of polluting industries is calculated by the authors from the Annual China Industry Economy Statistical Yearbook and the China Emission Accounts and Dataset; GDP, population, and urbanization of trade partners are from the World Bank's World Development Indicators; the distances between China and other countries are from CEPII Gravity database.

Table 5
Baseline Estimation Results.

	(1)	(2)	(3)	(4)
Dependent variable	lnExports	lnExports	SharePol	SharePol
BRI × Post	−0.02	−0.02	1.26*	1.93**
	(−0.37)	(−0.40)	(1.69)	(2.24)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Obs.	1512	1512	1512	1512
No. partners	189	189	189	189
R-Squared	0.981	0.982	0.734	0.736

Note: This table reports the difference-in-differences estimates of the effects of the BRI policy on China's exports (lnExports) and the share of polluting industries in China's exports (SharePol). BRI is a dummy indicator for a BRI country as defined in Table 1. Post is a time dummy which equals one for the years after 2013 and zero for the years before 2014. Control variables include the logarithm forms of economic size (lnGDP) and population (lnPop), urban development (represented by the share of urban population in total population, Urb), and distance between the partner and China multiplied by the year dummy. Year FE and Country FE represent year and country fixed effects, respectively. Standard errors reported in parentheses are clustered at the country level. *, **, and *** Denote statistical significance at the 10%, 5% and 1% levels, respectively. Source of data: see text.

effect of imports, we further test whether the BRI policy affects China's import volume and the share of low-carbon products in imports. China's import data that is specific for its trade partners and products is derived from UN Comtrade Database. We employ the same models as the baseline regressions but replace the dependent variable with logarithm of import volume and share of low-carbon imports. The regression models are as followed:

$$lnImports_{dt} = \alpha + \beta BRI_d \times Post_t + X_{dt}\Gamma + \theta_d + T_t + \varepsilon_{dt} \tag{13}$$

$$ShareClean_{dt} = \alpha + \beta BRI_d \times Post_t + X_{dt}\Gamma + \theta_d + T_t + \varepsilon_{dt} \tag{14}$$

where the dependent variable $lnImports_{dt}$ is the log value of China's imports from partner d in year t, and $ShareClean_{dt}$ is the share of low-carbon products in China's imports from d in year t. BRI_d is a dummy indicator for a BRI country as defined in Table 1. $Post_t$ is a time dummy which equals one for the years after 2013 and zero for the years before 2014; X_{dt} is a vector of country-year-specific controls, θ_d and T_t represent destination and year fixed effects, respectively.

The results are shown in Table 6. The coefficients in Columns (1)–(4) are all positive but none of them are statistically significant, indicating that there is no evidence that the BRI policy has boosted China's import from the BRI countries, nor that it has encouraged China to import more low-carbon products. Furthermore, we limit the sample to intermediate products based on the classification by Broad Economic Categories (BEC) and the results remain unchanged (Table 7).

In conclusion, the BRI has no significant effect on import volume or share of low-carbon products in imports. Thus, our baseline results are robust even the impact of the structural change in China's imports is considered.

3.3. Mechanisms

In this section, we further analyze the mechanisms behind the aforementioned structure change in exports.

The Belt and Road Initiative has five priority areas: policy alignment, infrastructure connectivity, trade friction reduction, financial

Table 6
Estimation Results for Import Volume.

	(1)	(2)	(3)	(4)
Dependent variable	lnImports	lnImports	ShareClean	ShareClean
BRI × Post	0.08	0.06	2.12	2.08
	(0.66)	(0.51)	(0.98)	(0.82)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Obs.	1256	1256	1256	1256
No. partners	157	157	157	157
R-Squared	0.959	0.960	0.894	0.895

Note: This table reports the difference-in-differences estimates of the effects of the BRI policy on China's imports (lnImports) and the share of low-carbon products in China's imports (ShareClean). BRI is a dummy indicator for a BRI country as defined in Table 1. Post is a time dummy which equals one for the years after 2013 and zero for the years before 2014. Control variables include the logarithm forms of economic size (lnGDP) and population (lnPop), urban development (represented by the share of urban population in total population, Urb), and distance between the partner and China multiplied by the year dummy. Year FE and Country FE represent year and country fixed effects, respectively. Standard errors reported in parentheses are clustered at the country level. *, **, and *** Denote statistical significance at the 10%, 5% and 1% levels, respectively. Source of data: see text.

Table 7
Estimation Results for Intermediate Products.

	(1)	(2)	(3)	(4)
Dependent variable	lnImports	lnImports	ShareClean	ShareClean
BRI × Post	0.06	0.08	2.39	2.15
	(0.45)	(0.55)	(0.97)	(0.77)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Obs.	1208	1208	1208	1208
No. partners	151	151	151	151
R-Squared	0.953	0.955	0.870	0.871

Note: This table reports the difference-in-differences estimates of the effects of the BRI policy on China's imports (lnImports) and the share of low-carbon products in China's imports (ShareClean) only using the sample of intermediate products. BRI is a dummy indicator for a BRI country as defined in Table 1. Post is a time dummy which equals one for the years after 2013 and zero for the years before 2014. Control variables include the logarithm forms of economic size (lnGDP) and population (lnPop), urban development (represented by the share of urban population in total population, Urb), and distance between the partner and China multiplied by the year dummy. Year FE and Country FE represent year and country fixed effects, respectively. Standard errors reported in parentheses are clustered at the country level. *, **, and *** Denote statistical significance at the 10%, 5% and 1% levels, respectively. Source of data: see text.

integration, and personnel exchanges. Among them, infrastructure connectivity has been a key investment area of China's outward investment. Notably, China's international project contracting (CIPC) with the BRI countries, which mainly involves large-scale construction of government-led infrastructural projects,[17] has been increasing continually since the Belt and Road Initiative was implemented. In addition, the Chinese government encourages its domestic firms of all ownership types - including private firms - to increase investment in the BRI countries, which also contributed to the rapid growth of China's outward foreign direct investment (OFDI) to the BRI countries after 2013. Using the enterprise-level data from Global Enterprise Greenfield Investment Database, Lyu et al. (2019) find that the implementation of the Belt and Road Initiative has significantly increased the investment of sectors related to infrastructure in the BRI countries. As shown in Fig. 5, the values of CIPC and the OFDI stock increased continually after 2013, amounting to US$98 billion and US$180 billion in 2019, respectively.

The infrastructure projects mostly involve massive building materials (such as cement and steel) and energy (such as coal, oil, gas and electricity) investments that belong to carbon-intensive industries, causing a concern about the pollution footprint of the BRI countries' imports from China. If this is the case, the CO_2 emissions in China will increase. To check whether the two influencing mechanisms are valid or not, we construct the following regression models:

$$SharePol_{dt} = \alpha + \beta_1 BRI_d \times Post_t \times M_{dt} + \beta_2 BRI_d \times Post_t + \beta_3 BRI_d \times M_{dt} + \beta_4 Post_t \times M_{dt} + \beta_5 M_{dt} + X_{dt}\Gamma + \theta_d + T_t + \varepsilon_{dt} \tag{15}$$

where M_{dt} are China's international project contracting with partner d in year t in logarithmic form ($lnCIPC_{dt}$), a dummy variable for

[17] Transportation construction, general construction, and power engineering are the main business areas of China's international project contracting. They mostly involve massive building materials (such as cement and steel) and energy (such as coal, oil, gas and electricity) investments which belong to highly polluting industries.

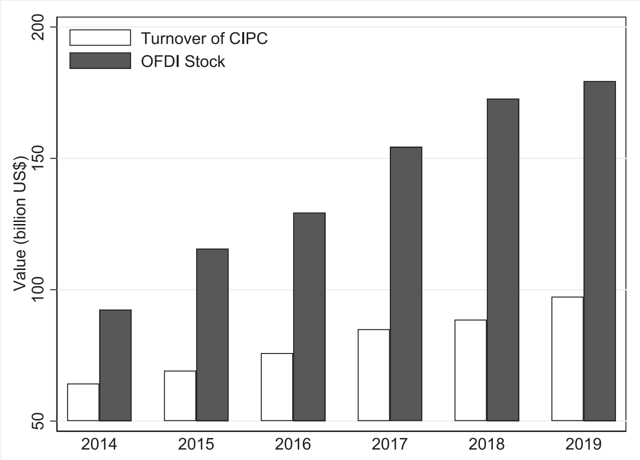

Fig. 5. Values of CIPC and Outward Investment to the BRI Countries (2014–2019).
Note: The x-axis is for years. The y-axis represents the turnover of China's international project contracting (CIPC) and the stock of China's outward foreign direct investment to the BRI countries. The hollow bars are the turnover of CIPC to the BRI countries, and the solid bars represent OFDI stock to the BRI countries. Source of data: CIPC data is from the Statistical Bulletin on China International Project Contracting, and the OFDI stock data is from the Statistical Bulletin of China's Outward Foreign Direct Investment.

CIPC ($CIPC\_dummy_{dt}$), China's OFDI stock in logarithmic form ($lnOFDI_{dt}$) and a dummy variable for OFDI to partner d in year t ($OFDI\_dummy_{dt}$), respectively. The dummy variable $CIPC\_dummy_{dt}$ equals one if the CIPC of partner d in year t is bigger than the median of CIPC for all the countries in year t, and zero otherwise; likewise, the dummy variable $OFDI\_dummy_{dt}$ equals one if OFDI of partner d in year t is larger than the median of OFDI for all the countries in year t, and zero otherwise. All other variables are the same as in Eqs. (11) and (12). The CIPC data is collected from the Statistical Bulletin on China International Project Contracting, and the OFDI stock data is from the Statistical Bulletin of China's Outward Foreign Direct Investment. The triple interaction term here is intended to capture how the BRI effect estimated in Eqs. (11) and (12) hinges on the levels of international contracted projects and OFDI.

The estimation results are listed in Table 8. Columns (1)–(2) report the effects of CIPC on the pollution intensity of China's exports to its partners. With all controls included and the standard errors clustered at country level, the coefficient of $BRI_d \times Post_t \times lnCIPC_{dt}$ in

Table 8
Mechanism Tests.

	(1)	(2)	(3)	(4)
	SharePol	SharePol	SharePol	SharePol
	M = lnCIPC	M = CIPC_dummy	M = lnOFDI	M = OFDI_dummy
BRI × Post× M	0.55**	3.39**	0.15	0.17
	(2.04)	(2.41)	(0.51)	(0.76)
BRI × Post	−3.10	0.03	1.17	1.41
	(−1.12)	(0.03)	(0.60)	(0.92)
BRI × M	−0.55	−1.80	0.25	1.38
	(−1.55)	(−1.16)	(0.59)	(1.16)
Post × M	−0.51***	−2.97***	−0.14	−0.98
	(−2.90)	(−3.36)	(−0.61)	(−1.09)
M	0.63**	1.20*	−0.08	−1.14
	(2.44)	(1.92)	(−0.30)	(−1.22)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Obs.	1327	1327	1392	1392
No. partners	170	170	176	176
R-Squared	0.793	0.793	0.772	0.773

Note: This table reports the mechanisms tests of the effect of the BRI policy on the pollution intensity of China's exports. The dependent variable is the share of polluting industries in China's exports (SharePol) in all columns. BRI is a dummy indicator for a BRI country as defined in Table 1. Post is a time dummy which equals one for the years after 2013 and zero for the years before 2014. M in columns (1)–(4) are China's international project contracting in logarithmic form, a dummy variable for CIPC, China's OFDI stock in logarithmic form), and a dummy variable for OFDI, respectively. Control variables include the logarithm forms of economic size (lnGDP) and population (lnPop), urban development (represented by the share of urban population in total population, Urb), and distance between the partner and China multiplied by the year dummy. Year FE and Country FE represent year and country fixed effects, respectively. Standard errors reported in parentheses are clustered at the country level. *, **, and *** Denote statistical significance at the 10%, 5% and 1% levels, respectively. Source of data: see text.

Columns (1) and the coefficient of $BRI_d \times Post_t \times CIPC\_dummy_{dt}$ in Columns (2) are both positive and statistically significant at the 5% level. Columns (3)–(4) show how OFDI affects the pollution intensity of China's exports to its partners. The coefficients of $BRI_d \times Post_t \times lnOFDI_{dt}$ in Columns (3) and the coefficients of $BRI_d \times Post_t \times OFDI\_dummy_{dt}$ in Columns (4) are both positive but statistically insignificant even at the 10% level. These findings suggest that China's international project contracting is an important channel behind the rising share of polluting industries in China's exports to the BRI countries, whereas there is no direct evidence to support that China's outward foreign direct investment is an influencing channel.

As stated in Section 1, numerous scholars have used various OFDI datasets to investigate the effect of BRI policy on OFDI and the results vary greatly depending on the data used. To check the robustness of our results, we collect several OFDI data from different sources and rerun the regressions modeled in Eq. (15) with different OFDI indictors. All the results[18] show that there is no empirical evidence to suggest that OFDI is a channel behind China's increasing share of carbon-intensive goods exported to the BRI countries. Thereby, our results are robust.

There are two possible explanations for non-significant OFDI results. First of all, OFDI has two effects on exports: accelerating effect and substitution effect. On the one hand, an increase in OFDI will increase the market demand of the destination country and, to some extent, stimulate the exports of the host country. On the other hand, OFDI, particularly greenfield investment which directly builds new firms in the destination country, is likely to offset the exports of the host country by using local products instead of imports from the host country in order to reduce trade costs and boost local employment. When the two effects are combined, OFDI may have no impact on exports. Our results may just reflect the situation that the two opposite effects offset each other. Another possible explanation is that our data span is not long enough to capture the delayed impacts of OFDI. 90% of China's OFDI to the BRI countries consists of greenfield investments (Lyu et al., 2019). Greenfield investment launches a business from the ground up and it takes time for the impact to be reflected in export.

3.4. Robust tests

3.4.1. Parallel trend test

A basic assumption underlying the above identification strategy is the parallel trend between the treatment and the control groups. For this research, the parallel trend assumption means that if the BRI was not proposed, the changes in the pollution intensity of China's exports to the BRI countries and the NBRI countries should follow similar trends. We apply the event analysis framework to verify the parallel trend assumption by using the following equation:

$$SharePol_{dt} = \alpha + \sum_{\tau=2009,\tau\neq 2013}^{2016} \beta^{\tau} \cdot BRI_d \times Year_t^{\tau} + X_{dt}\Gamma + \theta_d + T_t + \varepsilon_{dt} \tag{16}$$

where $Year_t$ are the year dummy variables for which 2013 is the base year, β^{τ} are the parameters of interest, and all other variables are as defined in Eqs. (11) and (12). The parameter β^{τ} indicates whether the difference in the share of carbon-intensive exports changed between BRI countries and NBRI countries in year τ relative to 2013. If the corresponding β^{τ} for the pre-BRI period are statistically insignificant, then the parallel trend assumption is satisfied. Fig. 6 plots the estimated parameters β^{τ} and the 90% confidence intervals. It is seen that the trends between the two groups are statistically indistinguishable for the pre-BRI period, but begin to diverge after 2013. This result shows that the identification strategy in this paper satisfies the parallel trend assumption.

3.4.2. Placebo test

In order to further prove that our baseline results are not driven by omitted trends that are shared by some NBRI countries, we randomly assign the BRI status to conduct a placebo test. In our sample, China exports to 189 countries, among which 61 are the BRI countries and 128 are the NBRI countries. We now randomly select 61 countries out of these 189 countries as the treatment group, while the remaining 128 countries are the control group. We then replicate the random assignment by 1000 times and repeatedly estimate the full regression model as specified in Column (4) of Table 5. Fig. 7 reports the kernel density curve of the regression coefficients of the placebo test. It is observed that the estimated coefficients are all distributed around zero, and most *p*-values are >0.05, indicating that the statistically significant estimates we obtain in our baseline results do not exist in these artificially assigned treatments, and that they are exclusive to the real BRI treatment.

3.4.3. Instrumental variable estimations

Following Tsoutsoura (2015)'s practice of using instrumental variable strategy in quasi-natural experimental studies, we resort to an instrumental variable estimation to further check the credibility of the results against endogeneity concerns.

We construct the instrument based on whether a country had any trade posts along the historical Silk Road routes. Specifically, a dummy *Ancient_BRI* is created to differentiate the treatment group and control group. The dummy is equal to 1 if the country is along the ancient Silk Road routes, and zero otherwise. Then we instrument the interaction term (*BRI_Post*) using the interaction of *Ancient_BRI* and *Post*.[19] The validity of the instrumental variable relies on the following two premises: First, one of the main goals of the Belt and Road Initiative is to restore the glory of the ancient Silk Road. The list of countries along the Belt and Road routes largely

[18] The results of robustness check are included in the Appendix (see Table A4).

[19] Similar to the BRI dummy in our baseline models, the dummy *Ancient_BRI* itself is absorbed by country fixed effects.

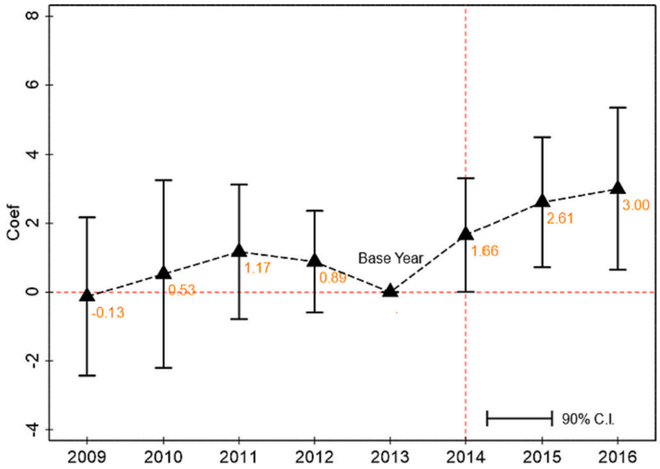

Fig. 6. Parallel Trend Test.
Note: This figure shows the key estimation result of Eq. (16). The dashed line with tringles represents the coefficients, and the solid line with caps is the 90% confidence intervals. Source of data: authors' calculations; see text for the original sources of data.

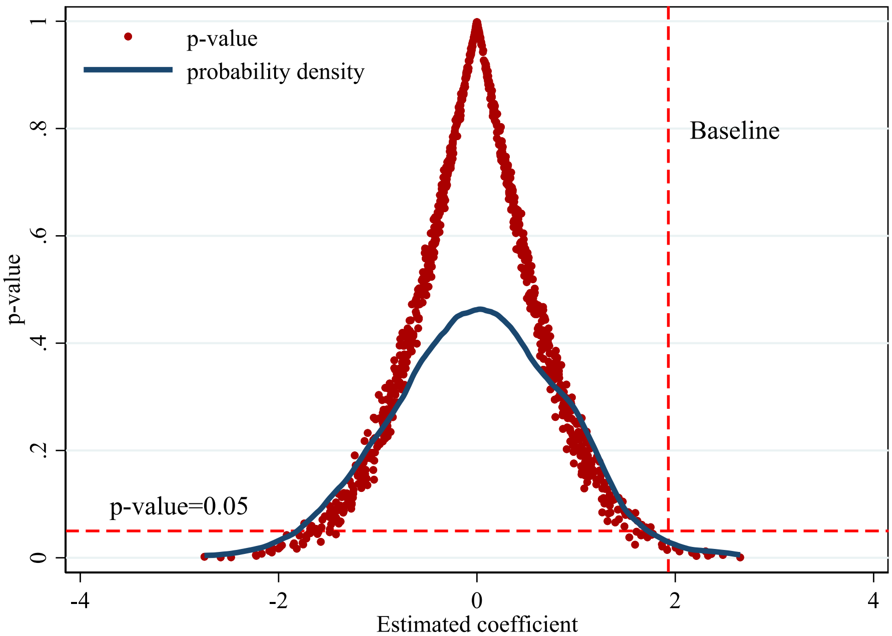

Fig. 7. Placebo Test (1000 replications).
Note:The red dots are the p-values of the key coefficients of Placebo test. The vertical dashed line is the coefficient of the key variable in the baseline result. Source of data: authors' calculations; see text for the original sources of data.

overlap with the list of countries along the ancient Silk Road,[20] hence, there is a positive correlation between the ancient Silk Road country status and the current Belt and Road country status. Second, it is well understood that the routes of the ancient Silk Road were predetermined by historical factors, and conditional on our baseline controls including country and year fixed effects, are unlikely to have an effect on the current economic variables other than through the current BRI status.

This article follows three seminal studies to define the ancient Silk Road countries. The first source is the Silk Road Atlas of the

[20] It has two geographical components: "The Silk Road Economic Belt" and "The 21st Century Maritime Silk Road". "The Silk Road Economic Belt" inherited the route of Zhang Qian's mission to the Western Regions during the Han Dynasty, which formed the main routes of the Silk Road. "The 21st Century Maritime Silk Road" continued the route of Zheng He's voyages to the West Ocean during the Ming Dynasty, which opened up maritime routes of Silk Road.

China Silk Museum, a piece of authoritative work conducted by Shijian Huang, a renowned expert on the history of Sino-foreign exchanges (Zhao, 2005). The second source comes from the United Nations Educational, Scientific and Cultural Organization (UNESCO). UNESCO has sought to better understand the rich history and shared legacy of the historic Silk Road since 1988 by running an international project: "*Integral Study of the Silk Roads: Roads of Dialogue*". A map of the ancient Silk Road was made publicly available as a product of this project.[21] Third and more recently, China Map Publishing House, the only national-level map publisher in China, published a panoramic map of the ancient Silk Road and modern Belt and Road in 2017. We combine the above three sources of maps and identify 57 modern countries as the countries which were along the historical Silk Road routes. The names of these countries can be found in the Appendix (see Table A2).

We multiply the dummy variable of ancient Silk Road countries by Post ($Ancient\_BRI_d \times Post_t$) as the instrumental variable of $BRI_d \times Post_t$. As part of a two-stage least squares (2SLS) estimation process, the first-stage regression is as follows:

$$BRI_d \times Post_t = \alpha + \beta Ancient\_BRI_d \times Post_t + X_{dt}\Gamma + \theta_d + T_t + \varepsilon_{dt} \tag{17}$$

where $Ancient\_BRI_d$ is the dummy variable for the ancient Silk Road countries, and the definitions of all other variables are the same as in Eqs. (11) and (12).

Additionally, to test the exclusion restriction of the IV, we use the subsample for period 2009–2013 and build the following model,

$$lnExports_{dt} = \alpha + \beta Ancient\_BRI_d + X_{dt}\Gamma + T_t + \varepsilon_{dt} \tag{18}$$

$$SharePol_{dt} = \alpha + \beta Ancient\_BRI_d + X_{dt}\Gamma + T_t + \varepsilon_{dt} \tag{19}$$

where $Ancient\_BRI_d$ (being along the ancient silk road and route) is the independent variable, $lnExports_{dt}$ (logarithm of exports scale) and $SharePol_{dt}$ (share of carbon-intensive products in China's exports) are the dependent variables.

The regression results are reported in Table 9. When we control for year fixed effects in Columns (2) and (4), $Ancient\_BRI_d$ has no significant impact on either $lnExports_{dt}$ or $SharePol_{dt}$. Therefore, the exclusion restriction of IV is satisfied.

Table 10 provides the regression results of the 2SLS estimation. Columns (1) and (2) report the results of the first-stage regressions. The estimated coefficients of the instrument, $Ancient\_BRI_d \times Post_t$, are all positive and statistically significant at the 1% level no matter the controls are included or not. The F statistics are greater than the rule of thumb cutoff, which indicates that there is no problem of weak instrument. Overall, the relevance condition of the instrument is well satisfied. Columns (3)–(6) of Table 10 report the results of the second-stage regressions. According to the results in Columns (3)–(4), with and without controls, the estimated coefficients of the key variable, $BRI_d \times Post_t$, are not significant at the 10% level, indicating that the BRI policy has no impact on total exports of China. However, the estimated coefficients of $BRI_d \times Post_t$ in Columns (5) and (6) are all positive and statistically significant at the 5% level at least. The estimated coefficient in Column (6) indicates that the BRI policy contributes to an increase in the share of carbon-intensive products in exports of China by nearly 5 percentage points, which is more than twice that of the baseline result. This finding strengthens our baseline result and suggests that without a proper instrumentation strategy our baseline estimates could be regarded as a lower bound of the true impact.

The difference between the OLS and 2SLS estimate could be the result of omitted factors which affect the dependent variables and the likelihood of being a BRI country simultaneously. One example of such factors is international political competition. Countries who tend to be in the camp of political competitors of China are less likely to join the BRI. At the same time, these countries are more likely to import carbon-intensive products from China instead of domestic production when they face similar international pressure of global climate change as China.[22] As a result, the baseline OLS estimation is likely to underestimate the effect of BRI policy.

4. Conclusions

Since the inception of the Belt and Road Initiative by China, more attention has been placed on its impact on the environment of the BRI countries than China itself. However, this unprecedentedly ambitious Initiative also left a significant carbon footprint within China, a leading exporter and carbon emitter of the world. Without a systematic understanding of the environmental impact of this Initiative on China, it would then be impossible to use solid evidence to inform a range of important policies including climate co-ordination across countries.

In this paper, we start with a decomposition approach to evaluate the driving factors of the changes in CO_2 emissions embodied in China's exports to the BRI countries and the NBRI countries. The result pinpoints the scale effect as the primary contributing factor to the changes in the CO_2 emissions in both BRI countries and the NBRI countries before the Initiative was launched. The composition effect had little impact on the CO_2 emission changes before the Initiative for both groups, but its contribution became more prominent after the Initiative was implemented, especially for the BRI group.

Furthermore, we use econometric methods to evaluate the BRI's impact on China's export volume and structure to its partners. The

[21] https://en.unesco.org/silkroad/

[22] According to Shui and Harris (2006), US imports of goods from China cause a greater production of carbon dioxide than if the goods were made in the US. Zhang and Pan (2022) argue that China is a major producer of carbon emissions, not a consumer country, and has taken more carbon emissions responsibility for the world, and as a result the developed countries should take more shared carbon emission responsibility than the Production-Based Accounting (PBA) principle.

Table 9
Validity Tests of the Instrumental Variable.

	(1)	(2)	(3)	(4)
Dependent variable	LnExports	LnExports	SharePol	SharePol
Ancient_BRI	0.30*	0.23	1.52	1.66
	(1.75)	(1.11)	(1.19)	(1.14)
Controls	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Obs.	945	945	945	945
No. partners	189	189	189	189
R-Squared	0.782	0.783	0.103	0.103

Note: This table reports the validity tests of the IV(Ancient_BRI). The dependent variable is lnExports (logarithm of China's exports) in columns (1) and (2) and SharePol (share of polluting industries in China's exports) in columns (3) and (4), while lnExports (logarithm of exports scale) is the dependent variable for columns (3) and (4). Ancient_BRI is the dummy variable for the ancient Silk Road countries. Control variables include the logarithm forms of economic size (lnGDP) and population (lnPop), urban development (represented by the share of urban population in total population, Urb), and distance between the partner and China multiplied by the year dummy. Year FE represents year fixed effects. Standard errors reported in parentheses are clustered at the country level. *, **, and *** Denote statistical significance at the 10%, 5% and 1% levels, respectively. Source of data: see text.

Table 10
2SLS Estimation Results.

	(1)	(2)	(3)	(4)	(5)	(6)
	1st BRI×Post	1st BRI×Post	2nd lnExports	2nd lnExports	2nd SharePol	2nd SharePol
Ancient_BRI × Post	0.73***	0.52***				
	(12.90)	(6.06)				
BRI × Post			−0.05	−0.12	2.35**	4.60***
			(−0.57)	(−0.76)	(2.35)	(2.68)
Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1512	1512	1512	1512	1512	1512
No. partners	189	189	189	189	189	189
First-stage F	166.49	36.71				

Note: This table reports the 2SLS estimates of the effects of the BRI policy on China's exports and the pollution intensity of China's exports. The dependent variable is BRI×Post in columns (1) and (2), lnExports (logarithm of exports) in columns (3) and (4) and SharePol (share of polluting industries in China's exports) in columns (5) and (6). BRI is a dummy indicator for a BRI country as defined in Table 1. Ancient_BRI is the dummy variable for the ancient Silk Road countries. Post is a time dummy which equals one for the years after 2013 and zero for the years before 2014. Control variables include the logarithm forms of economic size (lnGDP) and population (lnPop), urban development (represented by the share of urban population in total population, Urb), and distance between the partner and China multiplied by the year dummy. Year FE and Country FE represent year and country fixed effects, respectively. Standard errors reported in parentheses are clustered at the country level. *, **, and *** Denote statistical significance at the 10%, 5% and 1% levels, respectively. Source of data: see text.

regression results do not offer any compelling evidence that the Belt and Road Initiative has boosted China's exports to the BRI countries. However, the Belt and Road Initiative has increased the share of polluting industries in China's exports to these partners by nearly 5 percentage points, which is approximately one quarter of the share of carbon-intensive exports to the BRI countries. In addition, we find that China's international contracted projects is the main channel which increase the share of China's carbon-intensive exports to the BRI countries, causing more carbon emissions in China, while China's outward foreign direct investment is not.

Our research has important policy implications for both China and the BRI countries. First, now that China has set out its decarbonization pathway for the next decades, the environmental cost of the BRI must be put into the country's policy equation when balancing its economic growth goals and carbon emission targets. One of the implications from our findings is that more attention should be paid to the carbon emissions of the infrastructure and CIPC projects, which are typically colossal in size, and energy intensive. Specifically, it would help reduce the domestic carbon emissions if the energy supply for new infrastructure projects could be transformed from conventional (fossil fuel based) energy to non-fossil energy to decrease the carbon emissions, and if the energy-saving and green technologies could be more widely adopted in the infrastructure projects to continuously improve the efficiency of energy use. Stricter ecological and environmental protection standards should be implemented for infrastructure projects in order to improve the environmental efficiency in the operation, management and maintenance.

Second, in light of the new global climate agreement reached in COP-26 and China's commitment to a greener domestic economy, it will be increasingly costly for China to maintain a trade portfolio that has a negative impact on its domestic environment. It is therefore imperative for BRI partners, especially the least developed countries, to have an active overhaul and strategic planning of the structure of their trade and investment relationship with China. It also helps to build a coordinated network climate governance network with the other BRI countries in order to achieve a more sustainable and greener development partnership. Through a joint adoption of common green standards and regulations, all stages of the supply chain, from production and distribution to consumption, could be placed under stricter regulations and scrutiny, therefore reducing the environmental impact of trade on all participating countries.

While our paper examines whether the Belt and Road Initiative has led to a more carbon-intensive structured exports from China, future research can also look at the BRI effect on the other side of the trade: considering whether the share of high-carbon products imported by the Belt and Road countries has become higher after joining the BRI, and further investigating whether the BRI countries are more inclined to import those high-carbon products from China than from other countries. Another promising avenue for future research is to use firm-level data to explore firms' response to the BRI. In particular, an investigation into how specific policy incentives (such as VAT exemptions for investments in BRI destinations) offered by local governments induce state and private firms' investment in traditional or greener technology will help uncover the micro mechanisms underlying the aggregate-level findings.

Disclaimer

The opinions and views expressed in the paper do not necessarily reflect those of the organizations the authors are affiliated with or receive funding from. All remaining errors are our own.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Existing worldwide I-O tables datasets.

Database	Reference year(s)	No. of Regions	No. of Sectors
GTAP	2004、2007、2011、2014	141	65
Eora	1991–2015	190	26
WIOD	2000–2014	43	56
OECD	2005–2015	71	34
EXIOBASE	1995–2011	44	163
AIIOTs	2005	19	76
ADB-MRIO	2018	24	15

Note: Source of data: authors' statistics based on the official website of each database.

Table A2
The list of the countries along the Ancient Silk Road.

Regions	Countries	Numbers
Africa	Egypt; Kenya; Somalia; Sudan	4
Europe	France; Greece; Hungary; Italy; Portugal; Rep. of Moldova; Romania; Russian Federation; Spain; Ukraine	10
Asia	Afghanistan; Armenia; Azerbaijan; Bangladesh; Bhutan; Brunei Darussalam; Cambodia; Dem. People's Rep. of Korea; Georgia; India; Indonesia; Iran; Iraq; Israel; Japan; Jordan; Kazakhstan; Kuwait; Kyrgyzstan; Lebanon; Malaysia; Maldives; Mongolia; Myanmar; Nepal; Oman; Pakistan; Philippines; Qatar; Rep. of Korea; Saudi Arabia; Singapore; Sri Lanka; Syria; Tajikistan; Thailand; Timor-Leste; Turkey; Turkmenistan; United Arab Emirates; Uzbekistan; Viet Nam; Yemen	43

Note: Somalia, Democratic People's Republic of Korea, Sudan, Syria, and Serbia are not included due to the lack of data. Source of data: see text.

Table A3
Classification and code of industrial sectors.

2-digit CIC	Name of sector	Abbreviation	Polluting
06	Coal Mining and Dressing	Coal Mining	1
07	Petroleum and Natural Gas Extraction	Petroleum	1
08	Ferrous Metals Mining and Dressing	Ferrous Metals	1
09	Nonferrous Metals Mining and Dressing	Nonferrous_Minging	1
10	Nonmetal Minerals Mining and Dressing	Nonmetal_Mining	1
13	Food Processing	Food processing	0
14	Food Production	Food production	1
15	Beverage Production	Beverage	1
16	Tobacco Processing	Tobacco	0
17	Textile Industry	Textile	0
18	Garments and Other Fiber Products	Garments	0
19	Leather, Furs, Down and Related Products	Leather_Furs_Down	0
20	Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products	Timber	0
21	Furniture Manufacturing	Furniture	0
22	Paper making and Paper Products	Paper	1
23	Printing and Record Medium Reproduction	Printing	0
24 + 42	Cultural, Educational and Sports Articles & Other Manufacturing Industry	Cultural_Other	0
25	Petroleum Processing and Coking	Petroleum_Coking	1
26	Raw Chemical Materials and Chemical Products	Chemical	1
27	Medical and Pharmaceutical Products	Medical	0
28	Chemical Fiber	Chemical Fiber	0
29 + 30	Rubber Products & Plastic Products	Rubber_Plastic	0
31	Nonmetal Mineral Products	Nonmetal Mineral	1
32	Smelting and Pressing of Ferrous Metals	Ferrous_Smelting	1
33	Smelting and Pressing of Nonferrous Metals	Nonferrous_Smelting	1
34	Metal Products	Metal Products	0
35 + 41	Ordinary Machinery & Instruments, Meters, Cultural and Office Machinery	Ordinary Machinery	0
36	Equipment for Special Purposes	Equipment	0
37	Transportation Equipment	Transportation	0
39	Electric Equipment and Machinery	Electric Equipment	0
40	Electronic and Telecommunications Equipment	Electronic_Tele	0
44	Production and Supply of Electric Power, Steam and Hot Water	Electric power	1

Note: Somalia, Democratic People's Republic of Korea, Sudan, Syria, and Serbia are not included due to the lack of data. Polluting is a dummy variable which equals one if the CO_2 intensity is larger than the median, and equals zero otherwise. Source of data: authors' calculations based on the data from the Annual China Industry Economy Statistical Yearbook, the China Emission Accounts and Datasets, and the UN Comtrade Database.

Table A4
Robustness Check with Different OFDI Data.

Dependent variable: share of carbon-intensive exports	(1)	(2)	(3)	(4)	(5)
	OFDI-flow	Overcapacity	Pollution	Greenfield	M&A
BRI × Post × OFDI	0.38	0.01	0.00	−0.02	−0.05
	(1.39)	(0.13)	(0.02)	(−0.37)	(−0.82)
BRI × Post	−0.34	1.92**	1.95**	2.24*	2.04*
	(−0.23)	(2.17)	(2.12)	(1.75)	(1.79)
BRI × OFDI	−0.32	0.02	0.00	−0.02	0.07
	(−1.31)	(0.59)	(0.03)	(−0.51)	(1.42)
Post × OFDI	−0.37*	0.00	−0.02	0.01	−0.00
	(−1.77)	(0.05)	(−0.49)	(0.13)	(−0.05)
OFDI	0.26	−0.01	−0.00	0.02	0.00
	(1.50)	(−0.20)	(−0.08)	(0.70)	(0.12)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Obs.	1151	1327	1512	1512	1512
No. partners	166	170	189	189	189
R-Squared	0.813	0.736	0.736	0.736	0.736

Note: 1) OFDI variable is in logarithmic form. 2) Columns (1) reports the results with OFDI measured in flow; columns (2) and (3) reports the results only using subsample of overcapacity and pollution sectors separately; columns (4) and (5) reports the results with OFDI measured as greenfield investment and merger & acquisition investment separately. 3) All other variables are the same as in Table 8. Source of data: see text.

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