Technical gap, trade partners and product mix evolution: how trading with China affects global CO2 emissions

Banie Naser OUTCHIRI
Jie HE
Technical gap, trade partners and product mix evolution: how trading with China affects global CO2 emissions

Banie Naser OUTCHIRI †
Jie HE ‡

August 2020

Abstract

Based on a highly disaggregated database (1033 products, 181 partners) that we have built in physical terms, we investigate the drivers of China’s environmental trade cost (measured by CO2 emissions) from 1995 to 2014. To do this, we first used the “material balance” method to estimate China’s environmental trade cost. Then, we applied a new procedure to identify the drivers of China’s environmental trade cost that contributes to a better understanding of the trade’s role in environmental issues. Finally, we employed additive index decomposition analysis to estimate the contribution of each driver and their statistical accuracy. The results show that China faces a significant environmental cost as a result of its trade integration. Over the period, China’s environmental trade cost first was constant and relatively low from 1995 to 2001, then increased sharply from 2001 to 2008 before falling in 2009 and restarting unstable growth between 2010 and 2014. The decomposition results show that the increase in China’s environmental trade cost is explained by the fact that China’s technical catch-up is no longer able to offset the foreign demand effect and the product mix effect of exports. This is mainly due to the sharp increase in foreign demand for Chinese products and the fact that China’s export structure is becoming dirty mainly due to China-North trade patterns. There are some evidences that dirty production has slowly shifted from rich countries (especially North) to China, and clean production has moved in the opposite way. This has become more important after China’s entry into the World Trade Organization (WTO) in 2001, more specifically since 2004. Therefore, our results are better explained by the pollution haven hypothesis.

JEL classification: F18, O13, Q56, Q54.

Keywords: Carbon intensity, Emissions embodied in trade, Product level physical database, Material balance method, Index decomposition analysis.

†Economic Department and GREDI, École de gestion, Université de Sherbrooke. Contact : banie.naser.outhiri@usherbrooke.ca
‡Economic Department and GREDI, École de gestion, Université de Sherbrooke. Contact : jie.he@usherbrooke.ca
1 Introduction

International trade leads to a geographic separation of consumers from pollution emitted during production, allowing consumers to shift the pollution induced by their consumption elsewhere. This has fueled the debate on the impact of international trade on the environment (see Grossman and Krueger, 1991; Antweiler et al., 2001; Copeland and Taylor, 2004; Cherniwechan et al., 2017). Grossman and Krueger (1991) propose a standard decomposition that reveals three channels through which international trade may affect the environment, namely scale effect, composition effect and technical effect. International trade generates growth in economic activity, which tends to damage the environment (scale effect), while production may shift towards dirty or clean technologies (technical effect). In the case of the composition effect, if trade is driven by comparative advantages, then this effect depends on countries’ comparative advantage in dirty or clean products. In this way, the pollution haven hypothesis (PHH) stipulates that international trade will lead dirty industries to move towards countries where environmental regulations are weak (such as Southern countries), while the factor endowment hypothesis (FEH) states that international trade allows countries relatively abundant in factors used intensively in dirty industries to attract more dirty industries (such as Northern countries assuming that dirty industries are capital intensive and these countries are capital abundant) (see Grossman and Krueger, 1991; Antweiler et al., 2001; Copeland and Taylor, 2004). Antweiler et al. (2001) argued that these two hypotheses, although contradictory, work together in each country, so the interaction of environmental comparative advantage (PHH) and traditional comparative advantage (FEH) will determine the impact of international trade due to the composition effect.

Therefore, international trade may entail environmental costs/gains (measured by emissions) for countries. This can be harmful at the global level if the PHH donates the FEH, as global CO2 emissions would increase sharply due to the fact that Southern countries generally have high emission intensities. To quantify the environmental trade cost/gain for a country, the EEBT (“Emissions Embodied in Bilateral Trade”) and the PTT (“Pollution terms of trade”) index are generally used (see Papadas and Vlassis, 2018). But, the EEBT which is an absolute measure unlike the PTT index\(^1\) is better suited for analyzes that seek to capture total displaced pollution (see Grether and Mathys, 2013). Indeed, EEBT is introduced by Muradian et al. (2002), and is defined as the difference between emissions embodied in exports (EEE) and those embodied in imports (EEI). Thus, a positive (negative) EEBT means that the country is a net emissions exporter (importer), and therefore this country faces an environmental trade cost (gain). This absolute measure provide a better understanding of the change in the absolute level of CO2 emissions due to international trade. The effects of international trade on both emissions and the effectiveness of climate policies have become increasingly important with globalization. In this sense, since EEBT represents the difference between production-based and consumption-based emissions inventory, it is becoming increasingly important in the debate on equity of responsibility in reducing CO2 emissions (see Munksgaard and Pedersen, 2001;

\(^1\)The PTT index is a relative measure that was initially proposed by Antweiler (1996). Grether and Mathys (2013) revise this index to take into account differences in emission intensities between countries and over time, as well as trade in intermediate goods. The PTT is a ratio of pollution intensity embodied in exports and imports. In general, a PTT greater than one means that exports are more polluting than imports (For details see Antweiler (1996); Grether and Mathys (2013) and Duan and Jiang (2017)).
This environmental concern becomes more important when we address China’s case. Indeed, China has gradually become the world’s factory since it joined the World Trade Organization (WTO) in 2001. China’s CO2 emissions seem to be closely linked to its high trade dynamics. China has been the world’s largest exporter and second largest importer since 2009 (Duan and Jiang, 2017) and has become the largest CO2 emitter since 2005 (WDI, 2017). In 2017 its territorial fossil fuel CO2 emissions reached 27.21% of global CO2 emissions, followed by the USA (14.58%) and India (6.82%) (Statista, 2019). It’s important to analyze China’s CO2 emissions embodied in international trade for at least two other reasons. The first is that CO2 is a global pollutant, so CO2 emissions are a worldwide concern, although they are emitted in China. The second is that China determined in June 2015 its national actions by 2030 that consist of reaching the peak of CO2 emissions by 2030 and trying to reach it earlier; and also to reduce CO2 emissions per unit of GDP by 60% to 65% compared to 2005 levels by 2030 (NDRC, 2015). In such a context where China assumes responsibility for reducing its territorial CO2 emissions, the impact of international trade cannot be neglected. Because international trade presents not only challenges to climate policy through carbon leakage and competitiveness concerns, but also potential solutions for reducing greenhouse gas emissions, for example through the use of cooperative trade agreements and technology transfer (Weber and Peters, 2009). Thus, identifying the drivers of China’s environmental trade cost is a key starting point for understanding how to successfully reduce CO2 emissions linked to international trade. This is particularly urgent in the current context, because if we hope to achieve the objective of the Paris Agreement at COP21, China’s contribution as the largest CO2 emitter country will be necessary.

In order to identify the drivers of China’s EEBT, after estimating China’s EEBT through the “Material balance” method, we decompose EEBT variations using an additive index decomposition analysis (the approach of Shapley (1953)/Sun (1998)). We have adopted a two-step decomposition strategy. The first part of the decomposition, unlike the standard separation of the EEBT into EEE and EEI widely used in the literature (see Xu and Dietzenbacher, 2014), we have separated the EEBT into real emission transfers and new emission creations (propose by He and Jacquemin (2016)). Real emission transfers capture the fact that trading partners may use trade imbalances to transfer part of their emissions into China (in case of positive real emission transfers) and vice-versa. New emission creations are due to Chinese exports and the technical gap between China and its partners. Therefore, if China has less efficient production techniques, its exports will increase EEBT through additional carbon creation (in case of positive new emission creations) and vice-versa. This is also known in the literature as the impact of China’s exports on global CO2 emissions (see Ding et al., 2018). Thus, Chinese exports increase global CO2 emissions if new emission creations are positive. This separation of EEBT provides a better understanding of the role of trade in carbon emissions. By this separation, we can analyze the relative importance of trade imbalances.

\[^2\]The objective of Paris Agreement at COP21 consists to make efforts to limit the increase in global average temperature to 1.5°C above pre-industrial levels, and this can be achieved by reducing global greenhouse gas emissions by about 45% in 2030 compared to 2010 and by achieving net zero emissions by 2050 (IPCC, 2018).
since Straumann (2003) mentioned that the EEBT is sensitive to trade imbalance, on one hand and that of technical gap on other hand. So, we consider the difference in carbon efficiency between China and its partners that appears to be directly related to the increase in carbon emissions at a time when carbon emissions and international trade are increasing simultaneously.

In the second step of the decomposition, new emission creations (real emission transfers) are decomposed into four effects: scale effect of exports (net exports), between-partner composition effect of exports (net exports), within-partner (between-product) composition effect of exports (net exports), and technical gap effect (partners’ technical effect). Indeed, (i) scale effect indicates the importance of China’s size in international trade over time; (ii) between-partner composition effect indicates that China’s trade is further shifted towards partners with high or low technical efficiency; (iii) within-partner (between-product) composition effect indicates that China’s trade is further shifted towards clean or dirty products (it measures the product mix effect); and (iv) technical gap effect indicates that China’s technical efficiency is generally improving faster or not than that of its partners, while partners’ technical efficiency indicates whether or not the partners improve their technical efficiency. In addition to these effects we capture the product net entry effect, which indicates whether the new products traded are more polluting than those that are no longer traded or not.

An exceptional database built from three different sources includes physical (kg) exports and imports of 1033 products between China and 181 partners from CEPII-BACI (2016), world average ecological footprint coefficients of 1033 products in kg of CO2/kg of product from Sato (2014b), and countries’ CO2 emission intensity ratios from 1995 to 2014 calculated with CO2 emission intensity (kg of CO2/USD) from WDI (2017). This level of sectoral and geographical disaggregation with a 20-year time series analysis that is unique to this study necessarily comes with a hypothesis on the evolution of ecological footprint coefficients. Indeed, to find a way to differentiate the product ecological footprint coefficients between countries, and over time, we have made the assumption that for a given country all products are subject to identical technical progress, which is reflected by the country’s technical progress. As mentioned by Liu and Wang (2009), the low availability of these coefficients imposes restrictions on studies such as ours. Although this hypothesis is questionable, it appears to be more likely in studies using China as case-study, since China is more likely to have the highest product ecological footprint coefficients. We discussed the necessity, and the impact of this hypothesis on our results throughout the paper. A sensitivity analysis of the results was performed in this respect.

The results show that the impact of Chinese exports on global CO2 emissions (i.e. new emission creations) has entailed a significant environmental cost for China as a result of its trade integration. Over the period, China’s environmental trade cost first was constant and relatively low from 1995 to 2001, then increased sharply from 2001 to 2008 before falling in 2009 and restarting unstable growth between 2010 and 2014. Therefore, China’s entry into WTO seems to be a turning point in the evolution of its environmental trade cost. Indeed, the rapid increase in China’s environmental trade cost, following its entry into WTO, is explained by the fact that China’s technological catch-up effect is no longer able to offset the foreign demand effect and the product mix effect of exports. This is mainly due to the sharp increase in foreign demand for Chinese products and the fact that China’s export structure is becoming dirty.
mainly due to China-North trade patterns. There are some evidences that dirty production has slowly shifted from rich countries (especially those in the North) to China, and clean production has moved in the opposite way. This has become more important after China’s entry into WTO, more specifically since 2004. Therefore, our results are better explained by the pollution haven hypothesis. This highlights the challenges of mitigating international trade-related emissions and how to improve the effectiveness of emission mitigation strategies. Indeed, China’s voluntary contributions under Paris Agreement are more likely to significantly reduce international trade-related emissions if they lead to a technological catch-up effect that outweigh the combined effect of export expansion and that of dirty export structure.

The rest of the paper is organized as follows: Section 2 presents the literature related to our study and how this paper attempts to contribute to this literature and Section 3 describes the methodology adopted for the EEBT inventory and the procedure for its decomposition. Section 4 first presents the data, and then makes a preliminary analysis of the aggregated trends, and Section 5 presents and discusses the main findings. Section 6 conducts a sensitivity analysis of the main findings, and the Section 7 presents the conclusion of the paper.

2 Literature review

This study overlaps between three literatures and contributes to these literatures on several levels. Firstly, our study refers to literatures that calculate emissions embodied in trade, especially for China (see for example Ding et al. (2018)). These studies were essentially based on input-output (IO) analytical framework to estimate emissions embodied in trade. The use of this framework can lead to estimation errors due to low geographical coverage/disaggregation.

IO analytical framework include: Single Regional Input-Output (Sonio), Bilateral Trade Input-Output (BTIO) and Multi Regional Input-Output (MRIO). The recommended and most widely used approaches are the BTIO (EEBT) and the MRIO (see Peters, 2008; Wiedmann et al., 2007, 2011). BTIO and EEBT share the same logic for the calculation of BTIO (EEBT) and MRIO to quantify CO2 emissions embodied in trade. Studies that have used the MRIO to capture emissions from trade include Ahmad and Wyckoff (2003); Peters and Hertwich (2008); Davis and Caldeira (2010); Peters et al. (2011); Wiebe et al. (2012) and Xu and Dietzenbacher (2014). Among those based on the BTIO we have for example: Dong et al. (2010) and Wu et al. (2016) for China-Japan trade, Shui and Harriss (2006); Du et al. (2011) and Zhao et al. (2016) for China-USA trade, Tan et al. (2013) and Jayanathakumar and Liu (2016) for China-Australia trade, He and Jacquemin (2016) for China-French trade, Yu and Chen (2017) for China-South Korea trade and Ding et al. (2018) for a more global study (China and 219 countries).

IO analytical framework is limited in terms of geographical coverage and sectoral disaggregation. Although in recent years efforts have been made to produce IO tables each year for some countries, there are problems with their reliability and the fact that they are not in physical data. Indeed, several databases exist: GTAP (voir https://www.gtap.agecon.purdue.edu/databases/default.asp), WIOD (http://www.wiod.org/home), OECD/WTO, ADB-MRIO, IDE-JETRO, Eora-MRIO, EXIOBAXE. The last five databases are accessible on http://www.wiod.org/otherdb. Among all these databases, only the high-resolution version of Eora-MRIO (full Eora) is very disaggregated (15909 sectors, 190 countries from 1990 to 2015) but with a mixed classification system preserving national IO table detail (see http://www.worldmrio.com/), with not perfectly balanced data, proxy IO table for some countries and inconsistent, especially for developing countries, and information is in current year (see http://www.worldmrio.com/documentation/faq.jsp). The simplified version (Eora26) has only a harmonized classification with 26 sectors. In recent years, the WIOD (World Input-Output Database) has been increasingly used. But, the environmental accounts, including the sectors’ energy consumption, CO2 emissions currently cover only 40 countries (27 European Union (EU) countries and 13 other major countries in the world) from 1995 to 2009 (2013 version). The WIOT (World Input-Output Tables) at current prices cover the same number of countries (40 countries) and 35 sectors from 1995 to 2011, but 43 countries (28 EU countries and 15 other major countries in the world) and 56 sectors from 2000 to 2014 (2016 Version). Most often the data are in...
(see Su and Ang, 2010; Ding et al., 2018), sectoral aggregation bias (see Wyckoff and Roop, 1994; Lenzen et al., 2004; Su et al., 2010; Lenzen, 2011; Sato, 2014a), and price effect (see Muradian et al., 2002; Sato, 2014a; Papadas and Vlassis, 2018). We contribute to this literature by using the “Material balance” method which allows us to use physical data to avoid any price effects. Also, the flexibility of this method allows us to consider the highest possible sectoral disaggregation (1033 products) to avoid aggregation bias. Our study has an advantage in terms of geographical coverage (181 countries) associated with a strong temporal dimension (20 years). So, this flexibility allows us to overcome the key sources of uncertainty related to IO methods, i.e. the potential bias mentioned above. EEBT approach, like the BTIO, is more effective in analyzing trade and climate policy issues where transparency is important while MRIO is more suitable for final consumption analysis (see Peters (2008) for more details). As Ding et al. (2018) point out, based on other authors, the BTIO (so the EEBT) has fewer potential inaccuracies compared to MRIO, they are considered preferable in monitoring bilateral emissions trade balances, explaining “weak” carbon leakage and analyzing the PHH.

Secondly, this paper belongs to studies on the relationship between international trade and environmental quality (see Grossman and Krueger, 1991; Antweiler et al., 2001), specifically with CO2 emissions as a measure of environmental quality (see Cole and Elliott, 2003). This literature has been strongly influenced by the work of Grossman and Krueger (1991). The latter were the first to mention that international trade affects the environment by increasing economic activity (scale effect), changing production techniques (technical effect) and changing the composition of trade (composition effect). In this context, the first analyzes used this standard decomposition in an econometric framework with data from a panel of countries or states/provinces to explain the impact of international trade on environmental quality (see Grossman and Krueger, 1991; Antweiler et al., 2001; Cole and Elliott, 2003). These analyzes have contributed significantly to the debate on the importance of PHH and FEH. According to the theoretical model of Copeland and Taylor (2004), the composition effect of trade (which determines PHH or FEH) should be the decisive factor of the final impact of trade on environment. But empirical evidences from several authors (see Grossman and Krueger, 1991; Antweiler et al., 2001; Cole and Elliott, 2003) show that the composition effect of trade is relatively small. Therefore, if it is assumed that trade is driven by comparative advantage, then this result indicates a small influence of trade on environment (see the review of Cherniwchan et al. (2017)). Frankel and Rose (2005) point out that these studies use both a trade and income indicator in the same estimation, while these two variables are endogenous. Studies (see Chintrakarn and Millimet, 2006; Managi et al., 2009; McAusland and Millimet, 2013) that take into account this endogeneity problem, following the methodology of Frankel and Rose (2005), also do not lead to a significant impact of trade on environmental quality.

An alternative to estimation methods would be to directly measure the composition effect (see Cherniwchan et al., 2017). Levinson (2009) proceeds in this way at the level of the US manufacturing sector by conducting a decomposition analysis of SO2 emissions at the industrial level. But it also concludes that the effect of trade is weak. Indeed, Levinson (2009) by monetary terms, which raises the problem of conversion into comparable data. Monetary data also require the assumption on exchange rates, using the market exchange rate or purchasing power parity. Studies have shown that the EEBT estimate is very sensitive to this assumption (see Sato, 2014a).
using data at the industrial level does not succeed in separating the intra (or within)-industry composition effect from the technical effect. This does not allow a clear identification of the technical effect, regardless of any change in composition within the industry (see Levinson, 2009, 2015). This distinction is important because if the intra-industry (or intra-country in case of countries or states/provinces studies) composition effect is substantial (PHH or FEH), the fact that it cannot be dissociated from the technical effect may bias the technical effect estimate. Also, in previous studies, due to the fact that the data are not highly disaggregated, composition effect only accounts for inter (or between)-country composition effect (for countries or states/provinces studies) or inter (or between)-industry composition effect (for industry level studies). All these could explain why the studies failed to reveal a substantial composition effect, because they failed to estimate the other part (or the entire part) of the composition effect. This may partially explain the lack of evidence in favor of PHH.

Considering that the econometric approach is less appropriate for quantifying displaced pollution, we used the alternative approach with high disaggregated bilateral trade data. So, our study goes beyond the standard decomposition by distinguishing between the between-partner composition effect from within-partner (between-product) composition effect and product net entry effect. In doing so, our study is consistent with the new literature (see Cherniwchan et al., 2017) that builds on Melitz (2003) to capture the effect of international trade on environmental quality. Because with a high sectoral disaggregation we take into account the heterogeneity of emission intensities within sectors. The distinction between the two composition effects allows us to contribute more effectively to the discussion on the PHH. As the within-partner (between-product) composition effect measures the impact of product mix changes, it will allow us to better understand the hypothesis (PHH or FEH) underlying our results. While the between-partner composition effect will allow us to understand the impacts of a shift from China-North trade to China-South trade or the reverse.

Thirdly, our study is linked to the literature on the additive index decomposition analysis (see Ang, 2004). It allows us to capture the contribution of each effect in the variation of EEBT. Unlike many studies that use the log mean divisia index (LMDI I) method especially when the number of drivers (effects) becomes high because of its simplicity, we used the Shapley (1953)/Sun (1998) (S/S) method for several reasons. S/S method is robust to non-positive values (see Ang, 2004), allows to estimate the effect accuracies (see Outchiri, 2020). Finally, Outchiri (2020) has shown that failure to take into account the net entry effect of products may lead to a bias when estimating the effects’ contribution and it may influence the accuracy of the decomposition results. This can lead to a misinterpretation of the decomposition results.

---

5This literature has revealed that, because of firm heterogeneity, it is useful to be able to separate the between-industry and within-industry composition effect on the one hand, and to be also able to separate the within-industry effect from firm’s net entry effect on the other hand. This will make it possible to dissociate the technical effect from any other composition effect and thus allow a more judicious interpretation of the technical effect (see Levinson, 2009, 2015; Cherniwchan et al., 2017). By analogy with this literature, it is clear that countries are heterogeneous, and this reasoning can be applied in the present case of product exchange between countries.

6Outchiri (2020) mentioned that the accuracy of the results of this method should improve with the number of drivers, because the accuracy of the estimated effects is positively correlated with the number of drivers. Generally, decomposition analyzes with more than three effects are considered as analyzes with a large number of effects since the S/S method becomes complicated (see Ang, 2004). Thus, in our case the method is well adapted and should give more precise results.
3 Methods

3.1 “Material balance” method

This method estimates the ecological footprint embodied in trade by multiplying the physical flows of exported and imported products by the product ecological footprint coefficients that are calculated by the product life cycle analysis (LCA) (see Muradian et al., 2002; Moran et al., 2009; Sato, 2014b). The EEBT estimated by this method is considered to be the ecological footprints embodied in the traded goods (see Turner et al., 2007; Sato, 2014b).

Let:

\[ EEBT_{ct} = \sum_{f} \sum_{p} \left[ \varphi_{cpt} X_{cpt}^f - \varphi_{fpt} M_{cpt}^f \right] \]  

Equation 1 presents China’s EEBT, where \( c, f, p \) and \( t \) represent respectively China, China’s trading partners, product and time. \( EEBT_{ct} \) represents CO2 emissions embodied in China’s (\( c \)) bilateral trade each year (\( t \)) from 1995 to 2014. \( X_{cpt}^f (M_{cpt}^f) \) represents the physical flows (kg) of China’s exports (imports) to (from) its partner \( f \) of product \( p \) at time \( t \). \( \varphi_{cpt} (\varphi_{fpt}) \) are the “adjusted” ecological footprint coefficients (kg of CO2/kg of product) of country \( c \) (\( f \)), for product \( p \), at time \( t \). The low availability of data on product ecological footprint coefficient and the non-uniformity of calculation methods (see Sato, 2014b), led Sato (2014b) to propose in her study the world average ecological footprint coefficient of product. For each product, the average is computed only with ecological footprint coefficients calculated using the “cradle-to-gate” boundary system from different years and different countries (see Sato, 2014b). Thus, a problem for time-series analysis is that world average ecological footprint coefficients of product only vary between products and do not vary between countries or over time. To find a way to differentiate the product ecological footprint coefficient between countries, and over time, we have made the assumption that for a given country all products are subject to identical technical progress, which is reflected by the country’s overall technical progress. So, the technology level does not vary across products within a country. Under this assumption, we will have:

\[ \varphi_{zpt} = \frac{\varphi_{zt}}{\varphi_{w0}} \times \varphi_{p} \]

Where \( Z = \{ c, f \} \) and \( \varphi_{zt}, \varphi_{ft}, \varphi_{w0}, \varphi_{p} \) represent respectively China’s emission intensity (kg of CO2/USD) in year \( t \), partner’s emission intensity (kg of CO2/USD) in year \( t \), world average emission intensity (kg of CO2/USD) in the base year (here 1995), and world average ecological

---

7Several calculation methods are used to calculate the ecological footprint coefficients: “cradle-to-gate”, “gate-to-gate” and “cradle-to-grave”. “cradle-to-gate” boundary system cover emissions from the partial life cycle of products from manufacturing process (cradle) to factory’s gate, before they are transported to consumer. While those using alternative boundary systems such as “gate-to-gate” take into account the use and elimination stages of the product and “cradle-to-grave” considers recycling. LCA guidelines are given by ISO standards. See Sato (2014b) for more details.

8As Sato (2014b) mentioned, an alternative to the lack of country’s CO2 emission intensity of product is to systematically adjust world average CO2 emission intensity of product, using weights that reflect a country’s average technological level. Generally, these weights are captured by country’s average carbon intensity (per GDP emissions), and this systematically adjustment has been applied by the GTAP to fill countries’ CO2 emission intensities gaps (see Sato, 2014b). But as you can probably guess, there are limits to this approach, especially regarding the cement-clinker product in China’s case (see Sato, 2014b), which we will address in our sensitivity analysis.

9It is a simple arithmetic average of the CO2 emission intensity of all countries in our database in 1995,
footprint coefficient of product (kg of CO2/kg of product). Since $\varphi_{zt}/\varphi_{w0}$ is a ratio without unit, then $\varphi_{zt}$ is in kg of CO2/kg of product. The ratio $\varphi_{zt}/\varphi_{w0}$ refers to a country’s relative technical efficiency, i.e. the country’s CO2 emission intensity relatively to the world-wide CO2 emission intensity average. If a country’s ratio is higher (lower) than one, then that country has a low (high) technical efficiency compared to the world average. The higher this ratio, the lower the country’s technical efficiency will be. These adjustments are questionable, but they are necessary and have important advantages, as we will argue throughout the paper\textsuperscript{10}. We will estimate the EEBT without this adjustment (see Equation 3) in order to discuss the relevance of this adjustment.

$$EEBT(SC)_{ct} = \sum_{f} \sum_{p} \left[ \varphi_{p}X_{cpt}^{f} - \varphi_{p}M_{cpt}^{f} \right]$$ (3)

Without this adjustment, the EEBT ($EEBT(SC)_{ct}$ in equation 3) only captures the scale and composition effect since the carbon intensities of the products ($\varphi_{p}$) are constant across countries and years.

### 3.2 EEBT decomposition strategy

#### 3.2.1 First step of EEBT decomposition

By replacing equation 2 in 1 and with few manipulations, we can divide equation 1 into two components as follows:

$$EEBT_{ct} = \sum_{f} \sum_{p} \left[ \frac{\varphi_{ct} - \varphi_{ft}}{\varphi_{w0}} \varphi_{p}X_{cpt}^{f} \right] + \sum_{f} \sum_{p} \left[ \frac{\varphi_{ft}}{\varphi_{w0}} \varphi_{p}X_{cpt}^{f} - M_{cpt}^{f} \right]$$ (4)

including China.

\textsuperscript{10}The difficulty to produce emission intensities that vary by country, sector and year is neither specific to our study nor specific to CO2 emission intensity. Grether et al. (2009) used information from various sources to compute SO2 emission intensities that vary across countries, sectors and years. They combine two different databases on SO2 emissions. One provides information on emissions disaggregated by country (62 countries for seven dirty sectors for 1990, 1995 and 2000) and the other contains data on emission intensities disaggregated by sector (28 ISIC 3-digit sectors for only USA and for only 1987). Based on some assumptions (see Grether et al., 2009), they combine this database with industrial output and employment database. This allowed them to impute emissions from clean sectors and to build six databases on emission intensities (per dollar or per employee). These SO2 emission intensities have been used by Grether et al. (2009) to perform a growth decomposition analysis in which global manufacturing emissions change is decomposed into scale, composition and technical effects. They have also been used by Grether et al. (2010) to decompose global SO2 emissions into scale, composition and technical effects by focusing on the link between trade and global SO2 emissions. In order to identify and analyze the five distinct components of the PTT index that they proposed, Grether and Mathys (2013) also used these SO2 emission intensities. Since in their analysis one fundamental condition for the analysis to be possible is that emission intensities must be specific for each sector in each country and over time. The authors showed that, among the five PTT effects they analyzed, differences in SO2 emission intensities across countries and over time appear to be the strongest determinants. This supports the importance to consider differences in emission intensities both between countries and over time as we seek to do in this paper. Grether et al. (2012) in their contribution on the debate on pollution haven at the worldwide level, they adjust the 1987 US emission intensities (per employee) by each country’s industry labor-output ratio for ten pollutants, in order to have emission intensities that vary across countries (48 countries) and sectors (79 ISIC four-digit sectors) for 1987. They admitted that : “It is clear that having emissions coefficients for only one year is a major drawback and that applying US coefficients to a large sample of countries that includes developed and developing countries is problematic.” (see Grether et al. (2012), pg 136).
To understand the motivation underlying this separation, let us take here the case of a surplus in the EEBT for a Southern country (example China) with a Northern country (example Japan). This surplus may first be explained by the relocation of part of the Northern country’s production. As a result, emissions that should have been emitted into Northern country are now transferred into the Southern country. This part of the EEBT represents the real emission transfers (Transfers$_{ct}$) due to trade imbalances and technical efficiency of the Northern country. This issue is important because Northern country can use its trade deficit to transfer part of its emissions out of its territory, particularly into Southern country. As it is a transfer, this will only contribute to the reduction of Northern country’s CO2 emissions, but will not reduce global CO2 emissions. In addition, if the Southern country has less efficient production technologies and export products to Northern country, the EEBT may increase due to additional carbon creation. The size of this additional emissions depends mainly on the difference in carbon intensity of the sectors concerned by the relocation of production between the country receiving them (here Southern country) and the country relocating them (here Northern country), and the quantity of products exported. This part of the EEBT represents the new emission creations (Creations$_{ct}$). This component is also known in the literature as the impact of China’s exports on global CO2 emissions (see Ding et al., 2018). It represents the difference between the “real” CO2 emissions embodied in China’s exports (real EEE) and the “virtual” CO2 emissions embodied in China’s exports (virtual EEE)$^{11}$.

### 3.2.2 Second step of EEBT decomposition

At first sight, Creations$_{ct}$ is affected by both the difference in “adjusted” ecological footprint coefficients and exports while Transfers$_{ct}$ is affected by both trade imbalances and partners’ “adjusted” ecological footprint coefficients. Following Grossman and Krueger (1991), exports and trade imbalances can be further broken down into several factors that allow a more in-depth analysis of the effect of China’s trade patterns for a better understanding of the evolution of China’s environmental trade costs (gains). To do this, the additive decomposition analysis seeks to decompose the variation of EEBT through its two components (Creations$_{ct}$ and Transfers$_{ct}$). Indeed, following Outchiri (2020), for each two years (current year and base year) we distinguish between existing products in both years, entering products (existing only

\[
\text{Creations}_{ct} = \sum_{f,p} \left[ \frac{\varphi_{ct}}{\varphi_{pt}} X_{ft}^p \right] - \sum_{f,p} \left[ \frac{\varphi_{ct}}{\varphi_{pt}} X_{ct}^f \right].
\]

$^{11}$ Creations$_{ct}$ refers to “virtual” CO2 emissions embodied in China’s exports and EEE$_{ct}$ represents “virtual” CO2 emissions embodied in China’s exports. The real EEE are calculated with China’s “adjusted” ecological footprint coefficients, while the virtual EEE are calculated with partners’ “adjusted” ecological footprint coefficients. The virtual EEE represent EEE under zero trade assumption (see Shui and Harriss, 2006; Tan et al., 2013; Jayanthakumaran and Liu, 2016; Yu and Chen, 2017; Ding et al., 2018). Indeed, under this assumption, countries must satisfy their needs by producing themselves, because there is no trade. Thus, in such a situation, China’s exports will be produced by its partners in order to satisfy their own demand. Therefore, the underlying logic of real EEE assigns responsibility of emissions to producing country (as in the Kyoto Protocol), while that of virtual EEE assigns responsibility of emissions to consuming country. Under the logic of assigning full responsibility to producers, countries can reduce their domestic emissions by importing instead of producing. This remains an important aspect in the discussion of emission inventory strategies and their impact on the effectiveness of climate policies. This discussion was unanimous on the fact that the inventory assigning responsibility to the consumer (consumption-based inventory) is more fair, but it has evolved towards a shared responsibility between producers and consumers. In a context of shared responsibility, the discussion raises a debate about how this sharing should be done, in other words what key should be used for sharing (Readers interested in this discussion can consult, for example, Munksgaard and Pedersen (2001); Ferng (2003); Lenzen et al. (2004); Bastianoni et al. (2004); Gallego and Lenzen (2005); Lenzen et al. (2007); Rodrigues et al. (2006); Peters (2008); Kitzes et al. (2009) and Lenzen and Murray (2010).
in current year) and exiting ones (existing only in base year). Equation 5 presents the variation of EEBT:

\[
\Delta \text{EEBT}_{ct} = \Delta \text{Creations}_{ct}^{Ex} + \Delta \text{Transfers}_{ct}^{Ex} + \left[ \frac{\text{EEBT}_{ct}^{En} - \text{EEBT}_{ct}^{So}}{\text{NEE}} \right]
\]

Where \(Ex, En\) and \(So\) are sets defining respectively the set of existing, entering and exiting products. \(\text{EEBT}_{ct}^{En}\) represents the EEBT due to the new products traded, called the entry effect. If the entry effect is positive (negative), then the new products traded contribute to the increase (decrease) in EEBT. \(\text{EEBT}_{ct}^{So}\) (or written differently \(\text{EEBT}_{ct}^{So}\)) is EEBT due to products that are no longer traded, called the exit effect. A positive (negative) exit effect signifies that products that are no longer traded help to decrease (increase) the EEBT. The difference between the two effects is the net entry effect (NEE)\(^{12}\). According to equation 4, but focusing on existing products and with some manipulations, the expression of the two components of this equation become:

\[
\text{Creations}_{ct}^{Ex} = \sum_{f} \sum_{p \in Ex} \frac{X_{ct}^{f}}{\text{Scale}_{ct}} \times \left( \frac{X_{ct}^{f}}{X_{ct}^{0}} \right) \times \left( \frac{T_{ct}^{f}}{T_{ct}^{0}} \right) \times \left( \frac{\varphi_{ct}^{f}}{\varphi_{ct}^{0}} \right) \times \left( \frac{\varphi_{pt}^{f}}{\varphi_{pt}^{0}} \right)
\]

\[
\text{Transfers}_{ct}^{Ex} = \sum_{f} \sum_{p \in Ex} (X_{ct} - M_{ct}^{f}) \times \left( \frac{X_{ct}^{f} - M_{ct}^{f}}{X_{ct}^{0} - M_{ct}^{0}} \right) \times \left( \frac{T_{ct}^{f} - M_{ct}^{f}}{T_{ct}^{0} - M_{ct}^{0}} \right) \times \left( \frac{\varphi_{ct}^{f}}{\varphi_{ct}^{0}} \right) \times \left( \frac{\varphi_{pt}^{f}}{\varphi_{pt}^{0}} \right)
\]

The variations of equations 6 and 7 give us \(\Delta \text{Creations}_{ct}^{Ex}\) and \(\Delta \text{Transfers}_{ct}^{Ex}\) of equation 5. Equation 6 presents the factors that influence the evolution of new emission creations, otherwise scale effect of exports (Scale\(_{ct}\)), between-partner composition effect of exports (Composition\(_{ct}^{1}\)), within-partner (between-product) composition effect of exports (Composition\(_{ct}^{2}\)) and technical gap effect (Technical\(_{ct}^{f}\)). Equation 7 introduces the factors that drive the change in real emission transfers, otherwise scale effect of net exports (Scale\(_{ct}\)), between-partner composition effect of net exports (Composition\(_{ct}^{1}\)), within-partner (between-product) composition effect of net exports (Composition\(_{ct}^{2}\)) and partners’ technical effect (Technical\(_{ct}^{p}\)). The within-partner (between-product) composition effect of export (net exports) reflect the product mix effect of exports (net exports). Indeed, (i) scale effect indicates the importance of China’s size in international trade over time, captured by changes in foreign demand (\(X_{ct}\)) and changes in trade imbalance (\(X_{ct} - M_{ct}\)); (ii) between-partner composition effect indicates that China’s trade is further shifted towards partners with the highest or lowest technical efficiency, captured by changes in partners’ share of China’s exports (\(\frac{X_{ct}^{f}}{X_{ct}^{0}}\)) and changes in partners’ share of China’s trade imbalance (\(\frac{X_{ct}^{f} - M_{ct}^{f}}{X_{ct}^{0} - M_{ct}^{0}}\)); (iii) within-partner (between-product) composition effect indicates that China’s trade is further shifted towards clean or dirty products, captured by changes in

\(^{12}\)In general, a positive (negative) net entry effect (NEE) means that the movements in and out of traded products contribute to the increase (decrease) in EEBT. But, the interpretation of NEE depends on the sign of the entry effect and that of the exit effect. For example, if both the entry and exit effects are positive, and NEE is positive, then this would mean that the emissions generated by trading new products (entry effect) exceed the emission reductions achieved by no longer trading some products (exit effect). However, a positive NEE with negative entry and exit effects will have a different interpretation. Indeed, this will imply that the emission reductions achieved by trading new products (entry effect) cannot offset the increase in emissions due to products that are no longer traded (exit effect).
China’s export structure of products to its partners \( \left( \frac{X_{ct}^f}{X_{ct}} \right) \) and changes in trade imbalance structure of products with its partners \( \left( \frac{X_{ct}^f - M_{ct}^f}{X_{ct}} \right) \); and (iv) technical gap effect indicates that China’s technical efficiency is generally improving faster or not than that of its partners, leading to a change in technical gap \( \left( \frac{\varphi_{ct}^f - \varphi_{ct}^0}{\varphi_{ct}^0} \right) \varphi_p \), while partners’ technical efficiency indicates whether or not partners improve their technical efficiency, captured by a change in \( \left( \frac{\varphi_{ft}^f - \varphi_{ft}^0}{\varphi_{ft}^0} \right) \varphi_p \). Equations 6 and 7 can be written depending on \( I = \{ \text{Creations, Transfers} \} \) as follows:

\[
I_{ct}^{Ex} = \sum_f \sum_{p \in Ex} Scale_{ct} \times Composition^1_{ct} \times Composition^2_{cpt} \times Technical^f_{cpt} \tag{8}
\]

The objective is to identify separately the contribution of each effect (factor) in the evolution of \( I = \{ \text{Creations, Transfers} \} \). To do this, we will apply the additive decomposition approach of Shapley (1953)/Sun (1998) to capture the contribution of each effect and we will use the proposition of Outchiri (2020) to estimate the accuracy of these effects. After decomposition, we will obtain a relationship in the following form:

\[
\Delta I_{ct}^{Ex} = \Delta I_{Scale} + \Delta I_{Composition 1} + \Delta I_{Composition 2} + \Delta I_{Technical} \tag{9}
\]

Depending on \( I = \{ \text{Creations, Transfers} \} \), the right-hand elements of equation 9 represent the contributions of each effect. The detailed decomposition approach and the equations corresponding to the eight (8) contributions in equation 9 are presented in Appendix B. If an effect is positive (negative), then that effect contributed to the increase (decrease) in \( I = \{ \text{Creations, Transfers} \} \) due to the change in that effect, all other things being equal, compared to the 1995 base year situation.

4 Data sources and aggregate trends

4.1 Data sources

The first database contains information on world average ecological footprint coefficients for each product \( \varphi_p \) in kg of CO2/kg of product, which are obtained from Sato (2014b) database. It is calculated by the partial life cycle bottom-up analysis, i.e. it covers the emissions of a partial life cycle of the product from manufacture to the factory’s gate before product is transported to the consumer. For example with 1028 products traded between China and its partners in 2014, the average of \( \varphi_p \) is 3.07 kg of CO2/kg of product with a standard deviation (standard error) of 4.76 (0.15) and a median of 2.58 kg of CO2/kg of product. These coefficients vary from 0 to 69.74 kg of CO2/kg of product. The second database comes from the World Bank (see WDI, 2017). We have extracted CO2 emissions and GDP data to calculate the CO2 emission intensity (Kg CO2/USD) of each country from 1995 to 2014. We use these emission intensities to calculate relative technical efficiency ratios. The last database is the BACI database produced by CEPII on bilateral trade. The CEPII-BACI (2016) version provides value (USD) and physical (ton) exports and imports disaggregated into product at HS 6-digit level between 225 countries from 1995 to 2014. The methodology adopted for data harmonization and

\[\text{Authors’ calculations with Sato (2014b) database.}\]
\[\text{http://wwPIIw.cepii.fr/cepii/fr/bdl_modele/presentation.asp?id=1.}\]
\[\text{Details on this database can be found in Gaulier and Zignago (2010).}\]
reconciliation makes the information in this database more accurate (Sato, 2014b). We have defined China in this study as the whole of mainland China, Macao and Hong-Kong. China as defined above exchanges with 215 countries, but we extracted bilateral data between China and 181 partner countries. The number of partner countries is determined by the availability of countries’ CO2 emission intensities over the period 1995 to 2014 in the World Bank database. To match the data of the ecological footprint coefficients that are disaggregated into products at the SITC classification level (revision 3, resolution 4-digit), we have aggregated the trade data from HS 6-digit to the SITC classification. We use physical trade data and the processing of this data has caused a loss of 9.56% (3.93%) of exports (imports) on average each year. Finally, our bilateral trade database between China and its 181 partners covers the period from 1995 to 2014, disaggregated into 1033 products. This makes this decomposition study the most disaggregated both at the product and geographical level with a strong time dimension.

4.2 Aggregate trends

Several explanations are given to explain the impact of trade on emissions. First, with trade, production is likely to shift to the South, which will lead to an increase in the environmental trade cost in the South. If this explanation is right, we must expect an expansion of China’s trade, especially an increase in exports (scale effect). Since China is a Southern country, we must also observe a growth in the share of China’s exports to Northern countries and a decrease in the share of China’s imports from these countries (between-partner composition effect). This would mean that production is moving from North to China. Figure 1 (upper-left graph) shows the evolution of Chinese exports and imports, as well as the evolution of North’s shares. We can note that exports and imports increased after 2001, but with a deficit of China’s trade balance (measured in weight). This deficit is increasing over the period, especially from 2001 onwards. The share of exports to the Northern countries fell sharply from 2001 onwards. The sudden sharp drop between 1998-1999 may be explained by the Asian crisis of 1998. So, in our case, although there is an expansion of trade, Figure 1 does not fully support this first explanation. Because physical production has not shifted from North to China but rather from South to China. Also, a downward trend is observed for the share of China’s imports from North until around 2007. But the decline is more dramatic for the share of exports to North. This means that, in terms of weight, China is trading more and more with the South than with the North, with a higher shift in production from the South to China than in the opposite way.

The second explanation has been suggested to us by the pollution haven hypothesis (PHH), which states that with trade, dirty production will move to Southern countries because these countries have less stringent environmental regulations than those of the North. With this explanation, we should expect a growth in the share of dirty exports, and especially a growth in the share of dirty exports in total exports to the North (within-partner composition effect or can also be called between-product composition effect). This is what Figure 1 seems to

\[16\]

To identify dirty and clean products, we use the direct approach suggested in Mani and Wheeler (1999). We ranked products according to their ecological footprint coefficient, then identified dirty products as the last percentile and clean products as the first percentile. The emission footprint coefficient of clean products (104 products) varies between 0-0.28 Kg of CO2/Kg of product and that of dirty products (104 products) varies between 5.5-69.74 Kg of CO2/Kg of product.
show. Figure 1 (upper-right graph) shows that there is a trend increase in the share of dirty exports (especially after 2001 with a decline after 2009), while the share of dirty imports is decreasing. Regarding the trade of clean products, the share of these products in exports shows a downward trend (especially from 2001) while their share in imports points to an upward trend. All this means that China’s export structure seems to be increasingly dirty, while its import structure appears to be increasingly clean. This seems to be explained more by the structure of China-North trade than by that of China-South trade. Indeed, the middle-left graph (Figure 1) shows that China’s exports to North are more and more dirty. We observe an upward trend in North demand for dirty products (except from 2011 onwards), while North demand for clean products follows a downward trend. The gap between the two Northern demands (i.e Northern demand for dirty and clean products from China) has increased considerably since 2001. It can also be noted that Chinese demand for Northern countries’ products is more and more clean. China’s import share of clean products from the North is increasing while that of dirty products is decreasing. Since China and South generally exhibit similar types of comparative advantage, it is difficult to predict the pattern of China-South trade, as can be seen in the middle-right graph (Figure 1). There is no such clear evidence in the case of China-South trade as there is in the case of China-North trade. Nevertheless, China-South trade tends to behave weakly like China-North trade. Thus, even if the pollution haven hypothesis seems to be relevant, it is difficult to believe that this hypothesis alone explains the change in China’s environmental trade cost. Because not only the shift of trade from China-North to China-South can matter, but also the China-South trade’s patterns, even ambiguous, may be relevant to explain China’s environmental trade cost depending on changes in countries’ emission intensities.

The third possible explanation is that trade between China and its partners is shifting towards dirty or clean technologies. Figure 1 (lower-left graph) is consistent with the argument that trade between China and its partners has been shifted on average towards cleaner technologies. The average emission intensity is declining in both the North and the South. Also, except for the period between 2001 and 2005, China’s emission intensity is decreasing. Indeed, before its entry into the WTO, China’s emission intensity declined much faster than that of its partners. After its entry into the WTO, China’s emission intensity increased unlike the average emission intensity of its partners from 2001 to 2005, before falling after 2005, but not as fast as before its entry into the WTO. We may also notice that China’s emission intensity is closer to the average emission intensity of Southern countries than that of Northern countries. The technical gap between China and the North as well as between China and the South is narrowing. Therefore, the technical progress (the technical effect or more precisely the technical gap effect), which seems to have been more accelerated in China, should contribute to reduce China’s environmental trade cost.

A more in-depth analysis allowing us to isolate the contributions of the different possible explanation channels to the change in China’s environmental trade cost will be essential in order to confirm (or infirm) the preliminary findings that we have emphasized in this session.
Note: The North (39 countries) includes Annex B and OECD countries without Chile, Mexico and Turkey, but including Singapore. The South represents the other 141 countries of China’s trade partners (see Appendix A). Clean products are the products of the first percentile (104 products) of the ecological footprint coefficient. Dirty products are the products of the last percentile (104 products) of the ecological footprint coefficient.
Source: Authors.

Figure 1: Aggregate trends

5 Results

5.1 Changes in EEBT: Do New creations or real transfers matter?

Before interpreting our results, it is useful to compare these results with those of the literature in order to support the validity of our hypothesis on the evolution of product ecological footprint coefficients. In this respect, Appendix C shows a comparative table of our results and those of Ding et al. (2018)\textsuperscript{17}. First, the main encouraging point is that our results and

\textsuperscript{17}Recently, Ding et al. (2018) used the IO framework (BTIO) to inventory emissions embodied in China’s trade from 2000 to 2014, with a geographical coverage of 219 countries/regions, a sectoral disaggregation of 19 industries, and non-physical data. But this geographical coverage was only possible by using the typical region substitution method (the non-competitive imports assumption). Indeed, as the study is based on WIOD, it only
those of Ding et al. (2018) generally show the same trend in the evolution of EEBT and new creations from one year to the next. This means that our results show the same general trend as in Ding et al. (2018). Second, our results are lower than those of Ding et al. (2018) (except for 2008 for EEBT and 2001 for new creations). Therefore, compared to Ding et al. (2018), our hypothesis tends to underestimate the inventory of EEBT and new creations. Apart from differences in computational approaches, geographical coverage and hypotheses, the differences can be explained by the very high level of sectoral disaggregation in our study, which aims to improve the accuracy of our results\(^\text{18}\). Nevertheless, our results can be considered similar to those of Ding et al. (2018), as in the literature there is greater variability in China’s EEBT results in a given year due to methodological differences, emission accounting principles, data sources and data processing (see the review of Zhang et al. (2017)). Thus, since Ding et al. (2018) have used monetary data, this comparison may help to dispel doubts about the use of the physical units in this document. Third, we estimated the EEBT without adjusting the ecological footprint coefficients (see EEBT(SC), Figure 2). Therefore, since the ecological footprint coefficients are constant, then EEBT(SC) captures only the scale effect and composition effect of the environmental trade cost. EEBT(SC) is not consistent with the literature (see Zhang et al., 2017; Ding et al., 2018), which means that the technical effect is significant when estimating China’s environmental trade cost. This means that not adjusting the ecological footprint coefficients may be an even more unlikely assumption than adjusting, and this would likely lead to a greater underestimation of EEBT. But what is interesting for us is that the adjustment of the ecological footprint coefficients does not change the trend of the EEBT, it only changes its amplitude (comparison of EEBT and EEBT(SC), Figure 2). All this therefore supports our hypothesis on the evolution of ecological footprint coefficients.

Figure 2 displays the trend of the EEBT and its two components (New creations and real transfers) from 1995 to 2014. The EEBT is positive over the entire period. This means that China is a net exporter of CO2 emissions. Because, the emissions embodied in its exports exceed those embodied in its imports. This is consistent with the conclusion of several studies (example Ding et al. (2018)) and supports the literature consensus that developing countries as has IO tables for 38 countries (27 European countries, 6 Asian countries, 4 American countries, 1 Oceanian country and zero African countries). Thus, the IO tables, energy intensities and CO2 emission factors of the 181 other countries/regions are imputed by those of the typical regions identified using the data from 38 countries. In addition, Ding et al. (2018) had to aggregate the 35 sectors of the WDIO database to match the sectoral classification of the 19 trade industry categories according to China’s bilateral trade industrial sectors. This study has made efforts to address one of the limits of the IO framework by extending geographical coverage, but it may face sectoral aggregation bias and price effect. Unlike our study, its objective was not a decomposition analysis.

\(^{18}\) Wyckoff and Roop (1994); Lenzen et al. (2004); Su et al. (2010) and Lenzen (2011) have shown that emissions embodied in trade may be sensitive to sectoral disaggregation level. Indeed, low sectoral disaggregation may lead to significant bias in the estimation of emissions embodied in trade. This is known in the literature as the sectoral aggregation bias (see Sato, 2014a). Wyckoff and Roop (1994) show that with aggregation from 33 sectors to 6 sectors, CO2 emissions embodied in manufactured imports of Canada, France, Germany, Japan and the United Kingdom from the United States are about 30% lower. With a Multi-Regional Input-Output (MRIO) applied to the case of Denmark, Lenzen et al. (2004) report that aggregation leads to an increase in the deficit of CO2 emissions embodied in trade from 0.3 to 3.3 Mt of CO2, which is 11 times higher than in the case of disaggregation. Su et al. (2010) investigate the case where input-output data are more disaggregated than energy consumption data, and they find that it is preferable to disaggregate energy consumption data to match the classification of input-output data. Lenzen (2011) studies the opposite case where input-output data are less disaggregated than environmental data. He concludes that disaggregating input-output data, even on the basis of limited real data, to match the classification of environmental data is preferable to aggregating environmental data in determining input-output multipliers. Thus, Lenzen et al. (2004) rightly point out that sector aggregation has a significant impact on results and is likely to generate significant errors.
a whole are net exporters of CO2 emissions (see Liu and Wang, 2009). The EEBT increased from 301.34 Mt of CO2 in 1995 to 1289.4 Mt of CO2 in 2014, with some disparity in the sub-periods. The EEBT analysis can be done over three distinct sub-periods. The first period from 1995 until China’s entry into the WTO in 2001 is characterized by EEBT’s stability. The second period, after China’s entry into the WTO until the financial crisis of 2008-2009, we can observe a spectacular growth of the EEBT. It increased from 272.71 Mt of CO2 in 2002 to 1300.97 Mt of CO2 in 2008 before falling drastically (742.46 Mt of CO2) in 2009. This can be explained by China’s entry into the WTO in 2001, which certainly accelerated its trade integration between 2002-2008. This integration was slowed down with the financial crisis, which led to the fall of the EEBT in 2009. The third period, the period after the financial crisis, is materialized by a restart of EEBT’s growth, but it is not as stable as in the previous period. The EEBT represent annually about 7% to 18% of China’s total CO2 emissions.

![Figure 2: EEBT, New creations and real transfers.](image)

Note: New creations represent new emission creations. Real transfers refer to real emission transfers. The sum of the two gives the EEBT. EEBT(SC) is EEBT without adjusting the ecological footprint coefficients. Source: Authors.

EEBT’s evolution is mainly determined by the evolution of new emission creations (see Figure 2). Over the study period, new emission creations account for between 83% and 158% of China’s EEBT. Thus, much of China’s EEBT is attributable to its export production due to its relative inefficiency in terms of CO2 emissions. This means that under zero trade assumption, China’s exports contribute to the increase in global CO2 emissions. For instance, over the study period, about 1.45% to 3.85% of global CO2 emissions are due to China’s exports. Regarding real emission transfers through the trade imbalances, before 2006, the latter contributed to reduce China’s EEBT. Otherwise, China was using trade in a positive way to reduce its CO2 emissions, by transferring part of its emissions embodied in trade to its partners’ territories. Although the situation has been reversed since 2005, the contribution of real emission transfers to the EEBT remains relatively small (see Figure 2). He and Jacquemin (2016), over the period 1996-2005 in the context of China-France trade, also concluded that real emission transfers made a small contribution (around 1-2%) to the EEBT. Consequently, China’s trade imbalances
appear to have a negligible effect on its environmental trade cost.

As we mentioned on the one hand a difference between China-North trade and China-South trade, and on the other hand a difference between the trade of dirty and clean products, so the aggregated results in Figure 2 may show some disparities according to country group or product group. Figure 3 depicts graphs on this concern. We can also see in Figure 3, as in Figure 2, that the adjustment of ecological footprint coefficients does not change the trend of the EEBT, it only changes its amplitude (comparison of EEBT and EEBT (SC)). China’s trade of clean products contributes to reduce its EEBT (this remains valid both with EEBT (SC) or EEBT), thanks to a negative and increasing real emission transfers that exceeds in absolute value the new emission creations (see Figure 3, lower-left graph). Thus, the trade of clean products, by helping China to increase its real emission transfers to its partners’ territory, appears to be one of the channels by which China reduces its emissions (EEBT) through trade integration. Since the average emission intensity of the partners has improved (see lower-left graph of Figure 1), we can say that China is importing more and more clean products than it exports (consistent with upper-right graph of Figure 1). While China’s trade of dirty products has strongly supported the increase in EEBT (this remains valid both with EEBT(SC) and EEBT), thanks mainly to new emission creations, reinforced by the real emission transfers (see Figure 3, lower-right graph). Emissions embodied in China’s bilateral trade of dirty products are largely due to new emission creations (between 72.15% and 96.83%), and they represent between 23% and 51.23% of EEBT. The fact that the real emission transfers are positive means that, unlike the trade of clean products, the trade of dirty products contributes to reducing the real emission transfers from China to its partners.

These differentiated results between trade of clean and dirty products are consistent with the idea that China has gradually specialized in dirty production at the expense of clean production with its integration into international trade. This conclusion provides a first indication of the possibility of pollution haven that we have already noted in the section 4.2. To be considered as evidence of pollution haven, the differentiated results observed between trade of clean and dirty products must be due to China-North trade patterns. Although this can only be achieved by the decomposition analysis results in this study, for preliminary analysis we examine the trend of the EEBT and its two components by partner subgroups (North and South). The results of China-North trade (see Figure 3, upper-left graph) clearly exhibit the same trends as in Figure 1 (this remains valid both with EEBT(SC) and EEBT), suggesting that the China-North trade patterns are the most influential in the evolution of China’s EEBT and its two components. As in the case of Figure 1, EEBT between China and North are largely driven by new emission creations (between 87.69% and 170.33%), and they represent between 52.21% and 86.39% of EEBT. China-South trade has also contributed to the increase in China’s EEBT (see Figure 3, upper-right graph), but to a lesser extent than the China-North Trade.

### 5.2 Driving forces for changes of EEBT: Do PHH or FEH matter?

In this section, we will focus on the determinants of EEBT related to new emission creations for three reasons. First, the new emission creations are the largest part (between 83% and
Note: New creations represent new emission creations. Real transfers refer to real emission transfers. For each graph, the sum of the two gives the EEBT. EEBT(SC) is EEBT without adjusting the ecological footprint coefficients.

Source: Authors.

Figure 3: EEBT, New creations and real transfers by country and product groups.

158%) of the EEBT and they determine the evolution of the EEBT. Second, according to Table 3 of Appendix D, except for the between-partner composition effect from 2011 to 2014, all other estimated effects related to new emission creations are statistically significant. Third, compared to new emission creations, the effects related to the real emission transfers are not significant for several years, especially for the partners’ technical effect (see Table 4 of Appendix E). In addition, there is a strong instability in the evolution of the effects related to real emission transfers (see the right-hand graph of Figure 4). Despite this instability, the Appendix E attempts to provide some interpretations in order to complete this results analysis.

Figure 4 displays the four drivers of the new emission creations in the left-hand chart. As presented in Section 3.2.2, this figure is based on existing products, which allows effects to be properly interpreted, especially for the within-partner composition effect and the technical gap effect. The variations (as compared to 1995) of new emissions created confirm the result obtained with Figure 2. They are unsurprisingly positive and increasing after 2001.

First, China’s rapid export growth after its entry into the WTO until the financial crisis led to a positive and strongly increased in the contribution of export scale effect. After the financial crisis, this contribution peaked downwards before returning to a positive upward trend. For example, in 2014 compared to 1995, all other things being equal, the
Note: For the first chart on the new emission creations decomposition, the variation of creations is the annual variation (compared to 1995) of new emission creations (of existing products). This variation is decomposed into export scale effect (Scale), between-partner composition effect of exports (Between-partner composition), within-partner composition effect of exports (Within-partner composition) and the technical gap effect (Technical gap). With regard to the second chart on real emission transfers, the variation of transfers is the annual variation (compared to 1995) of real emission transfers (of existing products). This variation is decomposed into scale effect of net exports (Scale), between-partner composition effect of net exports (Between-partner composition), within-partner composition effect of net exports (Within-partner composition) and the partners’ technical effect (Technique of partners).

Source: Authors.

Figure 4: Decomposition results for new creations and real transfers.

increase in foreign demand for Chinese products increased new emission creations by about 153%, equivalent to an increase of 984 Mt of CO2. The fact that the export scale effect overcomes the changes in new emission creations means that if only foreign demand for Chinese products varies, then new emission creations should be more substantial than they are now.

Second, from 2004 onwards, the positive export scale effect is reinforced by a positive within-partner (between-product) composition effect. The positive and increasing contribution of the within-partner (between-product) composition effect shows that, all other things being equal, compared to 1995 China is exporting more and more products for which it has an environmental comparative disadvantage (less efficient in terms of emission intensity). In other words, the most efficient countries in terms of emission intensity are increasingly importing dirty products from China. In 2014 (compared to 1995 and all other things being equal), the contribution of this effect accounted for 46.18% (or about 297 Mt of CO2) of the changes in new emission creations. 78.53% of this contribution was due to products exported to Japan (38.98%), South Korea (19.16%), United States (9.80%), Italy (5.72%) and France (4.87%). At the same time, the five countries that contributed most negatively (about -7.37% of the changes in new emission creations) to the increase in this contribution were the United Arab Emirates, Australia, Panama, Congo and Nigeria. More generally, Figure 5 displays country specific within-partner (between-product) composition effect depending on country’s relative (to China) per capita income (lagged). It shows for each year\(^{21}\) the general trend of this effect and also the trend by country group.

\(^{21}\) We presented the graphs at two-year intervals starting in 1996 (the first year, because 1995 is no longer available after decomposition). We’ve added two special years, 2001 (China’s entry into WTO) and 2009 (2008-2009 financial crisis). But the conclusion drawn from this figure remains the same as that of all years.
(Northern and Southern countries). Before 2001, there is no clear evidence on the relationship between within-partner (between-product) composition effect and relative per capita income. But since 2001, the relationship has been strongly positive for the Northern countries and slightly negative for the Southern ones. The overall result is a positive relationship, indicating that the strongly positive relationship observed in the North dominates the negative relationship observed in the South. This confirms the fact that the Northern countries are more and more importing dirty products from China (see also Figure 1), so China’s export structure is becoming more and more dirty in favor of the Northern countries. This evidence reinforces our preliminary results presented in Sections 4.2 and 5.1, on the fact that dirty production has shifted from rich countries (especially those in the North) to China. Therefore, our results are better explained by the pollution haven hypothesis.

Note: Relative lagged income refer to the one period lag of country’s relative (to China) per capita GDP.
Source: Authors.

Figure 5: Country specific within-partner (between-product) composition effect, for New creations.

Thirdly, from 2004 onwards, the contribution of between-partner composition effect weakly reinforces the contribution of the export scale effect and the one of within-partner composition effect. The contribution of this effect is slightly positive from 2004 and not significantly different
from zero for the years 2011 to 2014. This means that the shift of trade from China-North to China-South is not so important in explaining the evolution of new emission creations. One possible explanation is that this trade shift is in favor of the richest Southern countries, which are supposed to be more efficient than China but less efficient than Northern countries in terms of emission intensity. In this case, the shift of trade will have little effect on new emission creations because this situation will make little difference in the technical gap between China and its partners, assuming that the efficiency of the richest Southern countries is close to that of the Northern countries. Analysis of the results of the two composition effects shows that the share of partner demand (between-country effect) does not determine the increase in the new emission creations, but it is the nature (clean or dirty) of the demand structure (between-product effect) that is decisive.

Fourthly, unlike these effects, the technical gap or technical catch-up effect is negative over the entire period. In other words, technical catch-up has contributed significantly to reduce new emission creations. In 2014 (compared to 1995), all other things being equal, the changes in technical catch-up reduced new emission creations by about 100% (equivalent to a reduction of about 644 Mt of CO2). This means that if, in 2014, only technical catch-up had varied, then the changes in new emission creations would have been zero, i.e. new emission creations in 2014 would have been equivalent to their 1995 value. In other words, if China’s trade patterns remain unchanged from those prevailing in 1995, then the technical catch-up could stabilize new emission creations. This important technical catch-up effect corroborates the results of Xu and Dietzenbacher (2014)\textsuperscript{22}. Indeed, they find that changes in China’s emission intensities have contributed significantly to reduce emissions embodied in exports and this contribution is greater than that of the world average. However, although the technical gap effect is generally increasingly negative over time, its effectiveness in helping to stabilize new emission creations has diminished over time following China’s entry into the WTO. Indeed, before China’s entry into the WTO (more precisely before 2004), the negative effect of technical catch-up was able to significantly offset the positive effect of foreign demand for Chinese products (export scale effect), thereby stabilizing new emission creations during this period. Over this period, both composition effects were slightly negative, reinforcing the technical gap effect. But, after China’s entry into the WTO, with the expansion of foreign demand for Chinese products and the positive contribution of both composition effects from 2004 onwards, the technical gap effect can no longer significantly compensate, leading to a sharp rise in new emission creations.

Finally, we summarize the results on the drivers of real emission transfers presented in the second chart of Figure 4 (see Appendix E for details) and also the results on the net entry effect (see Figure 9 of Appendix F). The real emission transfers from China to its partners are mainly through its trade deficits in terms of weight (the scale effect of net export). This channel was very decisive, especially before 2006, helping to achieve a real emission transfers from China to its partners. But from 2006 onwards, the situation was reversed (see Figure 2) due to the

\textsuperscript{22}Xu and Dietzenbacher (2014) used the MRIO with WIOD data (35 sectors, 40 countries and non-physical data) to analyze emissions embodied in global trade and also performed a decomposition analysis. They provided analyzes at the overall level, and at the specific level for two countries (USA and China). But, this study decomposes emissions embodied in trade through its two direct components (i.e. EEE and EEI), and as it is based on the IO framework with the MRIO it uses structural decomposition analysis. We can also note a low sectoral disaggregation and a low geographical coverage.
within-partner (between-product) composition effect, which has become positive since 2003 with an upward trend. Therefore, this effect has gradually reduced the real emission transfers from China to its partners, which means that China’s net export structure has become increasingly dirty since 2003. This is consistent with the fact that China’s export structure is increasingly dirty (exports more and more dirty products and exports less and less clean products) while that of its imports is increasingly clean (imports more and more clean products and imports less and less dirty products) (see Section 4.2). In an attempt to provide further explanation, we display the correlations between countries’ relative incomes and countries specific within-partner (or between-product) composition effects. This led us to conclude that within-partner composition effect appears to reflect an increasingly smaller real emission transfers from China to its richest partners, especially since 2006. This means that China’s increasingly dirty net export structure seems to be due to trade between China and its richest partners. Regarding product entry and exit effects\textsuperscript{23}, Appendix F shows that new products traded between China and its partners generate more CO2 emissions than the reduction of CO2 emissions from products that they no longer trade, especially in 2001 and 2014 (see Figure 9).

5.3 Driving forces for changes of EEBT: Do China-North or China-South trade matter?

We carried out the decomposition by country group (China-North trade and China-South trade) in order to provide a complementary analysis that will confirm or infirm the relevance of China-North trade patterns that we discussed above. In other words, this consists to provide an in-depth analysis of the PHH. In this sense, we are more interested in the contribution of within-partner (between-product) composition effects.

The upper-left chart (China-North trade) and that of upper-right (China-South trade) in Figure 6 report the decomposition results for new emission creations by country group. In general, regarding the drivers of new emission creations the decomposition results by country group are similar, but the contributions of each effect are different in terms of magnitude. Indeed, the scale effect of exports is positive and increasing (especially after 2001, with a fall in 2009) in both country group. After its fall in 2009, this effect has had a much stronger upward trend in China-South trade, leading to a stronger scale effect of exports in China-South trade than in China-North trade. But over the period, the trend of this effect in China-North trade remains similar to that of the overall decomposition. The technical gap effect is negative with a downward trend, and the between-partner composition effect of exports has a negligible contribution for both country group. The major difference between the results of this decomposition by country group comes from the within-partner (between-product) composition effect of exports. This effect in the case of China-North trade is positive and increasing since 2003 (as in the case of overall decomposition results in Figure 4 where it is positive and increasing since 2004), and much higher than that of China-South trade\textsuperscript{24}.

\textsuperscript{23}On average, each year we have 20 new products and about two (2) exiting products (compared to 1995) according to our database.

\textsuperscript{24}It should be recalled that the within-partner (between-product) composition effect of exports increased from 47.07 Mt of CO2 (in 2004) to 298.2 Mt of CO2 (in 2014) in the overall decomposition. In the case of China-North trade it increased from 61.26 Mt of CO2 (in 2003, with 41.65 Mt of CO2 in 2004) to 234.04 Mt of CO2 (in 2014). While in the case of China-South trade, the upward trend only started from 2007 onwards (with 5 Mt of CO2 in 2004), increasing from 25.56 Mt of CO2 (in 2007) to 46.65 Mt of CO2 (in 2014).
Therefore, China’s exports to Northern countries have been increasingly dirtier than China’s exports to Southern countries. More clearly, China’s exports to the North are increasing in products in which China has an environmental disadvantage (in the sense that China generally has higher emission intensities than its partners) over Northern countries. This result appears to support our previous conclusion that PHH would better explain our results than FEH.

For the drivers of real emission transfers, the upper-left chart (China-North trade) and that of upper-right (China-South trade) in Figure 7 show decomposition results by country group. The scale effect of net exports in both country groups are negative with a downward trend (since 2001 (1998) for China-North trade (China-South trade)). Therefore, in both cases, as in the overall decomposition, the scale effect of net exports is the key channel that has contributed to increase real emission transfers from China to its partners (from 2001 (1998) onwards for China-North trade (China-South trade)). Regarding the between-partner composition effect, as in the overall decomposition, the unstable variation of this effect does not allow for a useful interpretation, especially in the case of China-North trade. Since 2006, this effect has been negative with a downward trend in China-South trade. Therefore, from 2006 onwards, the between-partner composition effect of net exports has contributed to the increase in real emission transfers from China to Southern countries. Specifically, this means that since 2006, compared to 1995, China’s trade deficit with the most inefficient Southern countries (in terms of emission intensities) has become increasingly large. Thus, this has increased the real emission transfers from China to Southern countries through the most inefficient Southern countries. For the within-partner (between-product) composition effect, from 2003 onwards (as in the overall
Note: For each chart, the variation of transfers is the annual variation (compared to 1995) of real emission transfers (of existing products). This variation is decomposed into scale effect of net exports (Scale), between-partner composition effect of net exports (Between-partner composition), within-partner composition effect of net exports (Within-partner composition) and the partners’ technical effect (Technique of partners).

Source: Authors.

Figure 7: Decomposition results for real transfers by country and product groups.

decomposition), the contribution of this effect was positive with an upward trend in the case of China-North trade. In the case of China-South trade, however, this effect became clearly positive, with an upward trend only from 2006 onwards. This means that from 2003 (2006) onwards, in the case of China-North (China-South) trade, this effect has gradually reduced the real emission transfers from China to its partners. In other words, regardless of the country group, compared to 1995, China’s net export structure has become progressively less clean. Finally, the partners’ technical effect is negligible compared to the other effects in both cases. Nevertheless, in the case of China-North trade, this effect is mostly positive (except in 2007) with a slightly upward general trend as in the case of overall decomposition. So, the Northern partners’ technical effect has helped to reduce the real emission transfers from China to its partners, which means that the Northern partners’ technical efficiency has improved slightly on average over time. Before 2005, the same result is drawn with the Southern countries.25

As regards the net entry effects (see the upper-left chart (China-North trade) and that of upper-right (China-South trade) of Figure 10 in Appendix F), they are relatively small in both cases26, except for the years 2001 and 2014 for the case of China-South trade. Indeed, as the entry effects are positive (except in 2003 for the case of China-South trade), and the exit

25Obviously, because of the scale, the outcomes of partners’ technical effects are not clear in the charts. We have organized the charts in this way for better visualization in order to facilitate the results analysis. However, interested readers may request individual charts of each effect that are clearer.

26Before 2000, this effect is null in both cases because of the null entry and exit effects.
effects are positive (except in 2000 and from 2003 to 2007 for the case of China-North trade\textsuperscript{27}), so the positive net entry effect means that the emissions generated by trading new products (positive entry effect) exceed the emission reductions achieved by no longer trading some products (positive exit effect). In general, unlike in 2003 for China-South trade\textsuperscript{28}, movements in and out of traded products contribute to the increase in the EEBT of both China-North and China-South trade. Comparing these results with the overall results on net entry effect, it appears that movements in and out of traded products between China and the Southern countries seem to determine the overall evolution of the net entry effect and its two components (entry and exit effect), especially with regard to the entry effect in 2001 and 2014.

In light of the above analysis, comparing the decomposition results by country group to overall decomposition results, it stands out that, as in the case of EEBT (see the comparison of the upper-left and upper-right charts of Figure 3 to Figure 2), the China-North trade patterns are the ones that seem to drive the overall patterns of China’s bilateral trade.

5.4 Driving forces for changes of EEBT: Do clean or dirty products trade matter?

We performed the decomposition by product group (dirty products trade and clean products trade). The lower-left chart (Clean products trade) and that of lower-right (Dirty products trade) in Figure 6 display the decomposition results for new emission creations. For the trade of clean products, the scale effect of exports is positive and decreasing from 2003 (positive and increasing before 2003, and negative from 2009), both composition effects of exports became increasing from 2003-2004 (but became positive around 2007), and the technical gap effect is negative with an overall downward trend over the period (with an upward trend between 2001-2005). But the magnitude of these effects is very small, reflecting the marginal importance of new emission creations (see the lower-left chart of Figure 3) in the case of the trade of clean products. Regarding the trade of dirty products, the decomposition results for new emission creations are similar in terms of trend (but lower in terms of magnitude) to those of the overall decomposition, except for within-partner (between-product) composition effect of exports. The decomposition results show that two main effects work in opposite ways. The scale effect of exports is positive and strongly increasing, especially after 2001, with a fall in 2008-2009. The technical gap effect is increasingly negative (with a slightly upward trend between 2001-2005). After 2001, the scale effect of exports exceeds technical gap effect leading to a rapid increase in new emission creations as a result of production and export of dirty products. The two composition effects have very negligible contributions.

The lower-left chart (Clean products trade) and that of lower-right (Dirty products trade) in Figure 7 illustrate the decomposition results for real emission transfers. We noted above that

\textsuperscript{27}In 2000 and from 2003 to 2007 for China-North trade, the entry effect was positive while the exit effect was negative. In this case, the positive net entry effect implies that movements in and out of traded products between China and the Northern countries has contributed to reduce the EEBT because the emissions generated by trading new products (positive entry effect) are reinforced by the increase in emissions from products that are no longer traded (negative exit effect).

\textsuperscript{28}In 2003, the net entry effect of China-South trade was negative due to a positive entry effect that does not outweigh the positive exit effect. This means that in 2003 movements in and out of traded products between China and the Southern countries has contributed to reduce the EEBT because the emissions generated by trading new products do not exceed the emission reductions achieved by no longer trading some products.
the trade of clean products has contributed to reduce EEBT through increasingly negative real emission transfers (see the lower-left chart of Figure 3). This is mainly explained by the scale effect of net exports, which is increasingly negative (see chart 3 of Figure 7), indicating that net exports of clean products have increased real emission transfers from China to its partners. This means that, compared to 1995, China’s net exports of clean products are increasingly negative (i.e China exports less clean products than it imports). The partners’ technical effect has negligible contribution. Both composition effects are negligible until 2004, and then they show an unstable evolution which does not allow a useful analysis. Regarding the trade of dirty products, before 2005 no effect strictly dominates the others, and the effects are small (see the lower-right chart in Figure 7). After 2005, the technical effect remained relatively very small (negligible), while the two composition effects are unstable. But from 2007 onwards, the scale effect of net exports is positive with a constant trend. Thus, from 2007 onwards, China’s net exports of dirty products have led to a reduction in real emission transfers from China to its partners. This suggests that, compared to 1995, China’s net exports of dirty products are increasing (i.e China exports more dirty product than it imports).

The lower-left chart (Clean products trade) and that of lower-right (Dirty products trade) in Figure 10 (see Appendix F) show the results of net entry effect by product group. Over the period, the entry effect (exit effect) is zero for clean products trade (dirty products trade). From 2010 onwards, unlike 2009, the net entry effect of clean products trade was slightly positive due to a negligible negative exit effect which implies that movements in and out of traded clean products have slightly increased EEBT through clean products that are no longer traded. However, regarding the trade of dirty products from 2000 onwards, the net entry effect was positive thanks to positive entry effect. This means that movements in and out of traded dirty products have contributed to increase the EEBT through the emissions generated by trading new dirty products. Comparing these results by product group to the overall results, we can conclude that the trade of new dirty products has strongly contributed to the increase in the part of EEBT due to the trade of new products. This is important, because it suggests that if we do not consider the entry/exit effect, as this will be part of the technical effects, then the decomposition results will be biased (see Cherniwchan et al. (2017) and Outchiri (2020) for more details on this discussion). In our case, given the positive contribution of the entry effect of dirty products, this suggests that the technical effects are likely to be underestimated if we don’t properly consider the entry/exit effect.

6 Sensitivity analysis regarding cement-clinker case

Our strategy for adjusting ecological footprint coefficients, although necessary as discussed above, has limitations. One of the limitations is that it assumes that the technological level does not vary from one sector to another within a country. We may expect that this limit will have a limited impact on our results if we assume that the order of products according to their pollution intensity (ecological footprint coefficient) does not vary greatly from one country to another. We are also assuming that China is more likely to have the highest product ecological footprint coefficients. In general, given China’s coal consumption domination\(^{29}\), we can hope

\(^{29}\text{Data from China’s National Bureau of Statistics (NBS) and China Statistical Yearbook (CSY, 1999-2017) show that energy consumption is largely dominated by coal consumption, which represents on average about}\)
that this assumption is more plausible, at least in the case of pollution intensive products. But, this is a concern in the case of the cement-clinker product, since this sector is relatively newer in China and has more advanced and less polluting production techniques than some of its partners such as Canada, United Kingdom and United States (see Sato (2014b) for more details on this sector). Therefore, we perform a sensitivity analysis of our results that excludes this product from our analysis.

The ecological footprint coefficient of the cement-clinker product is 0.95 Kg of CO2/Kg of product. We recall that we have defined dirty products as those with an ecological footprint coefficient greater than 5.5 Kg of CO2/Kg of product, i.e. greater than the 90 percentile (the 10% most pollution-intensive products). While clean products are those with an ecological footprint coefficient below .28 Kg CO2 /Kg of product, i.e. below the 10 percentile (the 10% cleanest products). Thus, we can observe that the cement-clinker product is not a dirty products in our paper. The ecological footprint coefficient of the cement-clinker product is between the 20 percentile and the 30 percentile, which means that the cement-clinker product is closer to clean products than dirty ones. Also, the cement-clinker product represents, on average approximately 1.16% (.27%) of Chinese exports (imports) each year. This means that it is unlikely that this product will have a significant impact on our results. This is confirmed by our sensitivity analysis results presented in the Appendix G, which reproduces the entire analysis without the cement-clinker product. By comparing each graph in Figure 11 (see Appendix G) to the corresponding graph in the analysis including all products, we can see that our conclusions remain unchanged.

7 Conclusion and discussions

The purpose of this study was to assess China’s environmental trade costs and to investigate the drivers of their evolution. In this respect, we have built a highly disaggregated database (1033 products, 181 partners) from 1995 to 2014 in physical terms for analysis. We first adopted the “material balance” method, proposed by Muradian et al. (2002), to calculate the ecological footprint embodied in China’s bilateral trade in order to capture China’s EEBT. Then, we use a new decomposition process by first separating the EEBT into new emission creations and real emission transfers. From these two components, we identify nine (9) drivers of the EEBT’s temporal evolution, namely the scale effect of exports (net exports), the between-partner composition effect of exports (net exports), the within-partner (or between-product) composition effect of exports (net exports), the technical gap effect, the partners’ technical effect and the net entry effect of products. This new procedure contributes to a better understanding of the trade’s role in environmental issues. Finally, we employed additive index decomposition analysis (Shapley (1953)/Sun (1998) method) to estimate the contribution of each driver and their statistical accuracy.

The results show that China’s EEBT are always positive, which means that China is a net emission exporter (EEE are always higher than EEI). This is consistent with the conclusion of several studies on China (example Ding et al. (2018)) and supports the literature consensus that developing countries as a whole are net exporters of CO2 emissions (see Liu and Wang, 2018). 71% of total energy consumption every year (see http://www.stats.gov.cn/english/statisticaldata/annualdata/ for NBS and CSY data).
By extension our result is also consistent with the findings of studies using the PTT index (example Duan and Jiang (2017)). With positive EEBT, we may expect the PTT to be greater than one. The results of Duan and Jiang (2017) show that China’s PTT are always higher than one from 1995 to 2009, suggesting that China’s exports are always dirtier than its imports. In line with our first separation of the EEBT, the fact that China is always a net emission exporter is mainly determined by the impact of its exports on global CO2 emissions (i.e. new emission creations), especially after 2002. Over the period, China’s entry into the WTO seems to be a turning point in the evolution of its EEBT. As the new emission creations are the most important part in the evolution of EEBT, this means that the technical gap between China and its partners and/or China’s export patterns have changed between the period before and after its entry into the WTO. Indeed, before its entry into the WTO, China’s carbon intensity declined much faster than that of its partners (this was also noted by Duan and Jiang (2017)), this has led to a significant negative technical gap effect which has helped to stabilize the EEBT during this period. After its entry into the WTO, China’s carbon intensity increased unlike that of its partners from 2001 to 2005, before falling after 2005, but not as fast as before its entry into the WTO. However, the technical gap effect remained negative with a general downward trend. Since EEBT increased sharply after 2001 mainly due to new emission creations, this means that factors other than technical gap, such as China’s export patterns, have progressively started to play important roles. In this way, the decomposition results show that the sharp increase in China’s environmental trade cost (EEBT) after 2002 is explained by the fact that China’s technical catch-up is no longer able to offset the foreign demand effect (export scale effect) and the product mix effect of export (within-partner (between-product) composition effect of export). This is mainly due to the sharp increase in foreign demand for Chinese products and the fact that China’s export structure is becoming dirty. The fact that China’s export structure has increasingly become dirty is largely due to China-North trade. There are some evidences that dirty production has slowly shifted from rich countries (especially North) to China, and clean production has moved in the opposite way. This has become more important after China’s entry into the WTO in 2001, especially after 2004. Therefore, our results are better explained by the pollution haven hypothesis.

Our main results are consistent with the literature, aggregate trends, and sensitivity analysis. However, as data limitations have required some assumptions about carbon intensities in order to make the study possible, it is obvious that this remains the major drawback of this paper. Therefore, our results may be considered as a first attempt to contribute to the debate on the drivers of trade and environmental quality relationship by relying on a highly disaggregated physical database that allows us to overlook issues related to the IO framework. The high disaggregation of our data, made possible under our assumptions about carbon intensities, allowed us to properly estimate the two composition effects separately and also to consider the net entry effect. Indeed, as discussed in the literature review, with aggregated data we lose some heterogeneity of product emission intensities, and most often only the between-partner composition effect can be estimated and not the within-partner composition effect at product level. However, the between-partner composition effect appears to be negligible, while the

---

30 See Grether and Mathys (2013) for mathematical relationship between PTT and EEBT.
31 Often within-partner composition effect can be estimated but at the sectoral/industrial level depending on the level of aggregation. But as already discussed, aggregation can lead to biased results.
within-partner (between-product) composition effect seems to be more important and more suitable in the PHH and FEH discussion. Therefore, highly disaggregated and reliable data that vary over time, between countries and between products are needed for a more effective contribution to this discussion\textsuperscript{32}.

Our results have implications for emission mitigation strategies. There is no doubt that reducing emission intensities is a good starting point for hoping to reduce CO2 emissions. But in the case of international trade-related emissions, the results show that what matters in China’s case is to significantly reduce the technical gap. More precisely, the effect induced by China’s technical catch-up must outweigh the combined effect induced on the one hand by its export expansion and on the other hand by the fact that its dirty export structure is biased towards more efficient countries. This means that China’s voluntary contributions, in June 2015 to reduce CO2 emissions per unit of GDP by 60% to 65% compared to 2005 levels by 2030 (see NDRC, 2015), under Paris Agreement are more likely to significantly reduce international trade-related emissions if they lead to a technical gap effect that outweigh the combined effect of export expansion and that of dirty export structure. Thus, in China’s case it is relevant to take into account not only the partners’ capacity to reduce their emission intensities but also export’s features (especially that of China’s exports to North) in order to improve the effectiveness of emission mitigation strategies.

\textsuperscript{32}Grether and Mathys (2013) have argued in their analysis of the five components of the PTT index that differences in emission intensities over time, between sectors and between countries need to be addressed, based on richer databases. In this sense, the authors rely on the SO2 emission data constructed by Grether et al. (2009) under certain assumptions in order to have data that vary across countries, across sectors and over time. Their results revealed that, among the five PTT effects they analyzed, differences in SO2 emission intensities across countries and over time appear to be the strongest determinants. Along this line, they also suggest that better quality data on local pollutants are certainly needed for future analysis, especially that which varies between countries, between sectors and over time. Therefore, we reinforce and complete this suggestion by adding the global pollutant (CO2), and the need for a highly disaggregated data.
References


CEPII-BACI (2016). International Trade Database at the Product-Level.


WDI (2017). World Development Indicators database.


Appendix A  The countries covered by the study

Table 1: Country groups

<table>
<thead>
<tr>
<th>Group</th>
<th>Countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>Mainland China, Macao, Hong Kong</td>
</tr>
<tr>
<td>South (142 countries)</td>
<td>Afghanistan, Albania, Algeria, Andorra, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belize, Benin, Bermuda, Bhutan, Bolivia, Bosnia and Herzegovina, Brazil, Brunei Darussalam, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Chile*, Colombia, Comoros, Congo, Costa Rica, Cote d'Ivoire, Cuba, Cyprus, Democratic Republic of Congo, Djibouti, Dominica, Dominican Republic, East Timor, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Greenland, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Kyrgyzstan, Laos, Lebanon, Liberia, Libya, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico*, Micronesia, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Qatar, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Solomon Islands, South Africa, Sri Lanka, State of Palestine, Sudan, Suriname, Tajikistan, Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey*, Turkmenistan, Tuvalu, Uganda, United Arab Emirates, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.</td>
</tr>
<tr>
<td>North (39 countries)</td>
<td>Australia, Austria, Belgium-Luxembourg, Bulgaria**, Canada, Croatia**, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel*, Italy, Japan, Korea*, Latvia, Lithuania, Netherlands, New Zealand, Norway, Poland, Portugal, Singapore***, Slovak Republic, Romania**, Russia**, Slovenia, Spain, Sweden, Switzerland, Ukraine**, United Kingdom, UnitedStates*.</td>
</tr>
</tbody>
</table>

Note: (*) refers to OECD countries that are not Annex B countries, (**) indicates Annex B countries that are not OECD countries, and (*** ) represents the country that does not belong to Annex B countries or OECD ones. The North (39 countries) includes Annex B and OECD countries without Chile, Mexico and Turkey, but including Singapore. The South represents the other 142 countries of China’s trade partners.

Source: Authors.

Appendix B  The Decomposition Approach

From Ang (2004), in an additive decomposition approach there are two recommended methods depending on a zero residue decomposition and the data type (positive and/or non-positive). The first and most widely used in the literature is the additive log Mean Divisia Index I (LMDI I) introduced by Ang et al. (1998). But with the LMDI, weights are normalized to the unit (because they are always less than the unit) and logarithmic weights imply the assumption of a constant growth rate (Albrecht et al., 2002). In addition, the application of this method is complicated when data may be zero or negative because the weights associated with decomposition are in logarithms (see Ang and Choi, 1997; Ang et al., 1998; Wood and Lenzen, 2006; Ang and Liu, 2007a,b). With non-positive data in the case of additive decomposition, the recommenda-
tion of Ang (2004) suggests the use of Shapley (1953)/Sun (1998) (S/S) method. This method is robust to non-positive values without the need for data transformation. This method based on the Shapley value does not require any assumptions to provide perfect (i.e zero residue) decomposition (Albrecht et al., 2002). However, its formula becomes more complex with the number of effects to be decomposed, whereas the LMDI I formula is invariant to the number of effects to be decomposed (see Ang, 2004). But Ouchiri (2020) shows that we can use this feature of the S/S method to estimate the accuracy of the contribution of each effect. In contrast, this method should be used when the effects to be estimated are high, because the accuracy of the contribution of each effect is positively correlated to the number of effects (Ouchiri, 2020).

To simplify the formulas we set up the following:

\[ E_{ct} = \text{Scale}_{ct}, \ C1_{ct}^I = \text{Composition}_{1 ct}^I, \ C2_{cpt}^I = \text{Composition}_{2 cpt}^I \text{ and } T_{cpt}^I = \text{Technical}_{cpt}^I \]

Depending on \( I = \{\text{Creations}, \text{Transfers}\} \), equations 8 and 9 become:

\[ I_{Ex}^{ct} = \sum_I \sum_{p \in Ex} E_{ct} \times C1_{ct}^I \times C2_{cpt}^I \times T_{cpt}^I \]

\[ \Delta I_{Ex}^{ct} = \Delta I_{-Ect} + \Delta I_{-C1 ct} + \Delta I_{-C2 ct} + \Delta I_{-T ct} \]

The Shapley value applied to calculate the contribution of the scale effect of exports (or net exports) is as follows:

\[ \Delta I_{Ect} = \frac{s}{(s-1)!} \frac{(s-1)!}{(s-1)!} \sum_{S: Ect \in S; |S|=s} [I_{ct}^{Ex}(S) - I_{ct}^{Ex}(S - E_{ct})] \]

Where \( I_{ct}^{Ex}(S) \) the function as defined in equation 8. The elements of \( S^{33} \) use only the data from period \( t \), i.e. the current period. While all other elements use data from period 0, i.e. the base or previous period (here 1995). We have eight (8) possible definitions of \( S \):

\[ S = \{(E_{ct}), (E_{ct}, C1_{ct}^I), (E_{ct}, C2_{cpt}^I), (E_{ct}, T_{cpt}^I), (E_{ct}, C1_{ct}^I, C2_{cpt}^I), (E_{ct}, C1_{ct}^I, T_{cpt}^I), (E_{ct}, C2_{cpt}^I, T_{cpt}^I), (E_{ct}, C1_{ct}^I, C2_{cpt}^I, T_{cpt}^I)\} \]

Thus, the Shapley value becomes:

\[ \Delta I_{Ect} = \begin{cases} \frac{1}{4} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}) \\ \frac{1}{12} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}, C1_{ct}^I) \\ \frac{1}{12} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}, C2_{cpt}^I) \\ \frac{1}{12} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}, T_{cpt}^I) \\ \frac{1}{12} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}, C1_{ct}^I, C2_{cpt}^I) \\ \frac{1}{12} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}, C1_{ct}^I, T_{cpt}^I) \\ \frac{1}{12} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}, C2_{cpt}^I, T_{cpt}^I) \\ \frac{1}{12} \sum_{I} \sum_{p \in Ex} \Delta E_{ct} C1_{ct}^I C2_{cpt}^I T_{cpt}^I & \text{If } S = (E_{ct}, C1_{ct}^I, C2_{cpt}^I, T_{cpt}^I) \end{cases} \]

\(^{33}\text{Shapley called it the possible coalitions of } E_{ct} \)
With the additivity property, we can sum the eight (8) elements of the above equation. After arrangements, we have the following equation (which represents the contribution of the scale effect):

$$\Delta I_{E_{ct}} = \frac{1}{24} \sum_{f} \sum_{p \in E_{x}} (6 \times \Delta E_{ct} C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times \Delta E_{ct} C_{1}^{f} C_{2}^{f} T_{p}^{f})$$

$$+ 2 \times \Delta E_{ct} C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times \Delta E_{ct} C_{1}^{f} C_{2}^{f} T_{p}^{f} + 2 \times \Delta E_{ct} C_{1}^{f} C_{2}^{f} T_{p}^{f} + 6 \times \Delta E_{ct} C_{1}^{f} C_{2}^{f} T_{p}^{f}$$

The symmetry property allows us to derive the contribution of the other effects in the same way or directly from the contribution of the scale effect ($\Delta I_{E_{ct}}$). Therefore, we have the following equations:

$$\Delta I_{C_{1}^{f}} = \frac{1}{24} \sum_{f} \sum_{p \in E_{x}} (6 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f})$$

$$+ 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f} + 6 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f}$$

$$\Delta I_{C_{2}^{f}} = \frac{1}{24} \sum_{f} \sum_{p \in E_{x}} (6 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f})$$

$$+ 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f} + 6 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f}$$

$$\Delta I_{T_{p}^{f}} = \frac{1}{24} \sum_{f} \sum_{p \in E_{x}} (6 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f})$$

$$+ 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} C_{1,0}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f} + 2 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f} + 6 \times E_{c0} \Delta C_{1}^{f} C_{2}^{f} T_{p}^{f}$$

Since the sum of these contributions is equal to the decomposed aggregate (new emission creations or real emission transfers), then the decomposition will be perfect by construction. The P-values related to the contribution of each effect are estimated based on the approach proposed by Outchiri (2020). These P-values provide the statistical significance of the effects. To estimate these P-values, we applied the bootstrapped normal-approximation confidence interval (see Outchiri, 2020).
## Appendix C  Comparison of results with the literature

Table 2: Comparison with the results of Ding et al. (2018)

<table>
<thead>
<tr>
<th>Years</th>
<th>EEBT (Ding)</th>
<th>EEBT (Ding)</th>
<th>New creations (Ding)</th>
<th>New creations (Ding)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>301.34</td>
<td>-</td>
<td>418.19</td>
<td>-</td>
</tr>
<tr>
<td>1996</td>
<td>247.48</td>
<td>-</td>
<td>389.93</td>
<td>-</td>
</tr>
<tr>
<td>1997</td>
<td>303.08</td>
<td>-</td>
<td>418.79</td>
<td>-</td>
</tr>
<tr>
<td>1998</td>
<td>256.18</td>
<td>-</td>
<td>362.13</td>
<td>-</td>
</tr>
<tr>
<td>1999</td>
<td>372.55</td>
<td>-</td>
<td>399.37</td>
<td>-</td>
</tr>
<tr>
<td>2000</td>
<td>262.36</td>
<td>346.3</td>
<td>367.69</td>
<td>381.3</td>
</tr>
<tr>
<td>2001</td>
<td>269.31</td>
<td>317.2</td>
<td>365.66</td>
<td>349.6</td>
</tr>
<tr>
<td>2002</td>
<td>272.71</td>
<td>373.9</td>
<td>391.75</td>
<td>415.5</td>
</tr>
<tr>
<td>2003</td>
<td>409.94</td>
<td>534.9</td>
<td>529.47</td>
<td>591.0</td>
</tr>
<tr>
<td>2004</td>
<td>632.69</td>
<td>771.3</td>
<td>708.84</td>
<td>833.2</td>
</tr>
<tr>
<td>2005</td>
<td>802.50</td>
<td>995.6</td>
<td>824.81</td>
<td>1029.3</td>
</tr>
<tr>
<td>2006</td>
<td>1069.70</td>
<td>1159.9</td>
<td>1011.67</td>
<td>1161.0</td>
</tr>
<tr>
<td>2007</td>
<td>1284.73</td>
<td>1238.7</td>
<td>1132.42</td>
<td>1209.2</td>
</tr>
<tr>
<td>2008</td>
<td>1300.97</td>
<td>1048.2</td>
<td>1113.37</td>
<td>1017.0</td>
</tr>
<tr>
<td>2009</td>
<td>742.46</td>
<td>999.6</td>
<td>803.92</td>
<td>1008.3</td>
</tr>
<tr>
<td>2010</td>
<td>1082.37</td>
<td>1612.2</td>
<td>1041.78</td>
<td>1628.2</td>
</tr>
<tr>
<td>2011</td>
<td>1206.27</td>
<td>1676.8</td>
<td>1194.48</td>
<td>1710.8</td>
</tr>
<tr>
<td>2012</td>
<td>1175.67</td>
<td>1602.6</td>
<td>1129.35</td>
<td>1608.1</td>
</tr>
<tr>
<td>2013</td>
<td>1067.38</td>
<td>1495.2</td>
<td>1066.89</td>
<td>1460.6</td>
</tr>
<tr>
<td>2014</td>
<td>1289.46</td>
<td>1352.2</td>
<td>1071.15</td>
<td>1275.0</td>
</tr>
</tbody>
</table>

Note: The results of Ding et al. (2018) are taken from their paper in Table 3 for EEBT and Table 4 for new emission creations (new creations). In their paper EEBT is called NEEBT (Net CO2 emissions embodied in China’s bilateral trade) and new emission creations are known as impact of China’s export trade on global CO2 emissions (IEGE).

Source: Authors.
Appendix D  Other results for new emission creations

Table 3: Decomposition results for new creations and significance

<table>
<thead>
<tr>
<th>Year</th>
<th>Scale</th>
<th>Between-partner composition</th>
<th>Within-partner composition</th>
<th>Technical gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>10.54***</td>
<td>-3.823***</td>
<td>-8.466***</td>
<td>-26.52***</td>
</tr>
<tr>
<td>1997</td>
<td>88.41***</td>
<td>-9.694***</td>
<td>-3.548***</td>
<td>-74.57***</td>
</tr>
<tr>
<td>1998</td>
<td>49.01***</td>
<td>23.95***</td>
<td>-7.661***</td>
<td>-121.4***</td>
</tr>
<tr>
<td>1999</td>
<td>210.1***</td>
<td>-84.03***</td>
<td>36.65***</td>
<td>-181.5***</td>
</tr>
<tr>
<td>2000</td>
<td>169.4***</td>
<td>-15.99***</td>
<td>-20.08***</td>
<td>-222.0***</td>
</tr>
<tr>
<td>2001</td>
<td>184.0***</td>
<td>-15.99***</td>
<td>-14.56***</td>
<td>-196.3***</td>
</tr>
<tr>
<td>2002</td>
<td>230.4***</td>
<td>-15.99***</td>
<td>-14.56***</td>
<td>-196.3***</td>
</tr>
<tr>
<td>2003</td>
<td>352.0***</td>
<td>-14.46***</td>
<td>-10.19***</td>
<td>-215.9***</td>
</tr>
<tr>
<td>2004</td>
<td>430.0***</td>
<td>19.57***</td>
<td>47.07***</td>
<td>-207.4***</td>
</tr>
<tr>
<td>2005</td>
<td>523.4***</td>
<td>21.33***</td>
<td>65.52***</td>
<td>-208.3***</td>
</tr>
<tr>
<td>2006</td>
<td>702.4***</td>
<td>44.03***</td>
<td>90.82***</td>
<td>-249.6***</td>
</tr>
<tr>
<td>2007</td>
<td>853.2***</td>
<td>50.87***</td>
<td>142.5***</td>
<td>-337.4***</td>
</tr>
<tr>
<td>2008</td>
<td>820.5***</td>
<td>46.08***</td>
<td>180.4***</td>
<td>-356.5***</td>
</tr>
<tr>
<td>2009</td>
<td>479.3***</td>
<td>39.53***</td>
<td>180.1***</td>
<td>-318.8***</td>
</tr>
<tr>
<td>2010</td>
<td>727.3***</td>
<td>47.33***</td>
<td>237.6***</td>
<td>-394.6***</td>
</tr>
<tr>
<td>2011</td>
<td>856.4***</td>
<td>36.92***</td>
<td>297.1***</td>
<td>-418.7***</td>
</tr>
<tr>
<td>2012</td>
<td>882.9***</td>
<td>6.087***</td>
<td>299.9***</td>
<td>-482.0***</td>
</tr>
<tr>
<td>2013</td>
<td>870.2***</td>
<td>4.676***</td>
<td>293.5***</td>
<td>-523.8***</td>
</tr>
<tr>
<td>2014</td>
<td>982.4***</td>
<td>7.301***</td>
<td>298.2***</td>
<td>-644.0***</td>
</tr>
</tbody>
</table>

N = 456 456 456 456

Note: Main indicates that it is the observed means of the effects that are reported. Export scale effect (Scale), between-partner composition effect in exports (Between-partner composition), within-partner composition effect in exports (Within-partner composition) and the technical gap effect (Technical gap). 5000 bootstrap replications (** p < 0.01, * p < 0.05, p < 0.1).

Source: Authors.

Appendix E  Results of real emission transfers

Table 4 presents decomposition results of real emission transfers. As we can see, there are strong contributions of effects in 2013, which explains why the second chart of Figure 4 illustrates the evolution of effects from 1996 to 2012 to keep the chart lines from being flattened. The variations of real emission transfers, being most of the time positive (see the right-hand chart of Figure 4), show that, compared to the situation in 1995, China has gradually transferred less and less of its EEBT, through its trade imbalances, into its partners’ territory. Before trade liberalization (more precisely before 2004), except for the upward peak in 1999, the evolution of the changes in real emission transfers was relatively stable. After this period, the trend is sharply upward until the financial crisis of 2008-2009. This means that during this period China has been transferring a decreasing part of its emissions to partners. After the fall in 2009, certainly due to the financial crisis, there is an upward trend but less stable than in the previous period. Through which channels did these real emission transfers take place?

First, the contribution of the scale effect of net exports is negative, except for 1999, with a sharp downward trend. The contributions of this effect are statistically significant except for the years 2007 and 2010. This implies that, compared to 1995 and all other things being equal, the only change in net exports would have enabled China to gradually transfer a significant
part of its emissions to partners, via a trade deficit (measured in terms of weight). Thus, the fact that China’s imports weigh more than its exports over time has contributed to the transfer of part of its emissions out of its territory. In 2014, compared to 1995 and all other things being equal, the only change in net exports would have enabled China to transfer 677 Mt of CO2 out of its territory, i.e. in absolute terms more than twice the change of real emission transfers of the same year. Trade deficits (in weight) remain the key channel through which China uses trade to reduce its EEET. This channel was very decisive before 2006, helping to achieve a real emission transfers (which is negative) from China to its partners.

Table 4: Decomposition results for real transfers and significance

<table>
<thead>
<tr>
<th>Year</th>
<th>Scale</th>
<th>Between-partner composition</th>
<th>Within-partner composition</th>
<th>Technique of partners</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>-3.524***</td>
<td>-31.54***</td>
<td>11.67***</td>
<td>-2.191***</td>
</tr>
<tr>
<td>1997</td>
<td>-17.47***</td>
<td>119.7***</td>
<td>-109.4***</td>
<td>8.227***</td>
</tr>
<tr>
<td>1999</td>
<td>22.26***</td>
<td>17.87***</td>
<td>38.80***</td>
<td>11.11***</td>
</tr>
<tr>
<td>2000</td>
<td>-33.96***</td>
<td>-7.749***</td>
<td>28.07***</td>
<td>21.41***</td>
</tr>
<tr>
<td>2001</td>
<td>-70.80***</td>
<td>77.36***</td>
<td>-22.01*</td>
<td>25.80***</td>
</tr>
<tr>
<td>2002</td>
<td>-174.9***</td>
<td>330.9***</td>
<td>-202.2*</td>
<td>43.26***</td>
</tr>
<tr>
<td>2003</td>
<td>-160.1***</td>
<td>12.83*</td>
<td>104.9***</td>
<td>38.56***</td>
</tr>
<tr>
<td>2004</td>
<td>-146.6***</td>
<td>-91.54***</td>
<td>242.9***</td>
<td>34.19***</td>
</tr>
<tr>
<td>2005</td>
<td>-408.0***</td>
<td>588.9***</td>
<td>-129.2</td>
<td>42.27***</td>
</tr>
<tr>
<td>2006</td>
<td>-175.9***</td>
<td>19.55**</td>
<td>308.8***</td>
<td>21.53</td>
</tr>
<tr>
<td>2007</td>
<td>-111.6</td>
<td>8.639</td>
<td>385.8***</td>
<td>-14.19</td>
</tr>
<tr>
<td>2008</td>
<td>-256.6***</td>
<td>345.5***</td>
<td>198.0***</td>
<td>16.95</td>
</tr>
<tr>
<td>2009</td>
<td>-481.0***</td>
<td>-16.22</td>
<td>485.5***</td>
<td>64.90**</td>
</tr>
<tr>
<td>2010</td>
<td>-299.3</td>
<td>-328.7*</td>
<td>807.6***</td>
<td>-23.99</td>
</tr>
<tr>
<td>2011</td>
<td>-554.4***</td>
<td>-176.2***</td>
<td>794.0***</td>
<td>65.38</td>
</tr>
<tr>
<td>2012</td>
<td>-723.7***</td>
<td>-10.57</td>
<td>792.9***</td>
<td>104.2*</td>
</tr>
<tr>
<td>2013</td>
<td>-5087.8***</td>
<td>8327.3***</td>
<td>-4154.7**</td>
<td>1032.4*</td>
</tr>
<tr>
<td>2014</td>
<td>-677.0***</td>
<td>-135.0***</td>
<td>967.0***</td>
<td>144.2*</td>
</tr>
</tbody>
</table>

Note: Main indicates that it is the observed means of the effects that are reported. Scale effect of net exports (Scale), between-partner composition effect in net exports (Between-partner composition), within-partner composition effect in net exports (Within-partner composition) and partners’ technical effect (Technique of partners). 5000 bootstrap replications (***p < 0.01, **p < 0.05, *p < 0.1).
Source: Authors.

Secondly, although the between-country composition effect is most of the time significant (except for years 2007, 2009 and 2012), the unstable evolution of this effect does not allow us to bring out very useful information based on the right-hand chart of Figure 4. One explanation is that the sign of China’s trade imbalance with countries is not stable over a long period of time, which leads to an unstable effect. Thirdly, the within-country (between-product) composition effect are significant except for the years 1998 and 2005. Before 2003, the contribution of this effect is very unstable (especially with regard to the sign). But from 2003 onwards (except for 2013), the contribution of this effect was positive with an upward trend. This means that this effect has gradually reduced the real emission transfers from China to its partners. In other words, compared to 1995, China’s net export structure has become increasingly dirty. This is consistent with the fact that China’s export structure is increasingly dirty while that of its imports is increasingly clean (see Section 4.2). In 2014, compared to 1995 and all other things
being equal, the only change in the partners’ share of China’s net product exports has allowed a reduction in real emission transfers from China to its partners of 967 Mt of CO2, more than three times (324%) the global change of real emission transfers. This effect is the key factor explaining the positive real emission transfers observed from 2006 onwards (see Figure 2).

In an attempt to provide further explanation on within-partner composition effect, Figure 8 displays the correlations between countries’ relative income and countries specific within-partner (or between-product) composition effect. The overall trend is upwards, as well as within the South, especially since 2006. The trend in the Northern countries is not stable according to the years after 2006. Thus, this effect has contributed to reducing the real emission transfers from China to richer partners more than to other partners. Therefore, the fact that within-partner composition effect has gradually reduced the real emission transfers from China to its partners appears to reflect an increasingly smaller real emission transfers from China to richest partners, especially since 2006. This means that China’s increasingly dirty net export structure seems to be due to trade between China and richest partners. This has led to a greater reduction in the real emission transfers from China to richest partners than from China to other partners. This result is consistent within the South, but there is no clear evidence within the North.

Fourthly, the partners’ technical effect is significant except for the years from 2006 to 2008, 2010 and 2011. This effect is positive (except for 1996) and slightly increasing. This means that, compared to 1995 and all other things being equal, the only change in partners’ technical efficiency has reduced the real emission transfers from China to partners. This suggests that the partners’ technical efficiency has improved slightly on average over time. This is consistent with the evolution of the partners’ average emission intensities in Section 4.2. In 2014, compared to 1995 and all other things being equal, this effect has contributed to reduce by 144.2 Mt of CO2 the real emission transfers from China to its partners.
Note: Relative lagged income refer to the one period lag of country’s relative (to China) per capita GDP. Source: Authorss.

Figure 8: Country specific within-country (between-product) composition effect, for real transfers.
Appendix F  Entry effect, Exit effect and Net entry Effect

Note: Entry effect represents the change in EEBT due to new products traded. Exit effect represents the change in EEBT due to products that are no longer traded. The difference between them refer to Net entry effect. Source: Authors.

Figure 9: Entry effect, Exit effect and Net entry effect.

Note: Entry effect represents the change in EEBT due to new products traded. Exit effect represents the change in EEBT due to products that are no longer traded. The difference between them refer to Net entry effect. Source: Authors.

Figure 10: Entry effect, Exit effect and Net entry effect by country and product groups.

Appendix G  Sensitivity analysis regarding cement-clinker case

Figure 11 reports results (estimate of EEBT, new creations, real transfers, EEBT(SC), and decomposition analysis) excluding the cement-clinker product. Therefore, the charts in Figure
Illustrate the results, which are achieved without cement-clinker product, corresponding to those obtained with all products in Figure 2, Figure 4 and Figure 9.

Note: Results are achieved without cement-clinker product. The first chart presents the results of EEBT and its first two components (new emission creations and real emission transfers), as well as that of EEBT(SC). New creations represent new emission creations. Real transfers refer to real emission transfers. The sum of the two gives the EEBT. EEBT(SC) is EEBT without adjusting the ecological footprint coefficients. The second and third charts report the decomposition results of new emission creations and real emission transfers. Variation of creations is the annual variation (compared to 1995) of new emission creations (of existing products). This variation is decomposed into scale effect of exports (Scale), between-partner composition effect of exports (Between-partner composition), within-partner composition effect of exports (Within-partner composition) and the technical gap effect (Technical gap). Variation of transfers is the annual variation (compared to 1995) of real emission transfers (of existing products). This variation is decomposed into scale effect of net exports (Scale), between-partner composition effect of net exports (Between-partner composition), within-partner composition effect of net exports (Within-partner composition) and the partners’ technical effect (Technique of partners). The last chart shows the results of Net entry effect. Entry effect represents the change in EEBT due to new products traded. Exit effect represents the change in EEBT due to products that are no longer traded. The difference between them refers to Net entry effect.

Source: Authors.

Figure 11: All results without cement-clinker product.