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Contributing to better energy and environmental analyses: how accurate are decomposition analysis results?

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Abstract

This paper attempts to contribute to the improvement of decomposition analyses for better policy-making. This is achieved under Shapley (1953)/Sun (1998)'s approach, by taking into account the net entry effect of products. Indeed, we propose to estimate the standard errors of contributions using bootstrapped normal-approximation confidence interval in order to investigate whether or not effects are significantly different from zero at standard significance levels. Therefore, our work introduces a new criterion for the choice of decomposition approaches, so-called accuracy criterion. The application is based on a decomposition of CO2 emissions embodied in China's bilateral trade (EEBT). The results show that omitting the net entry effect can lead to under- or over-estimates of the contributions, wrong signs and even a wrong order of magnitude of the contributions, and incorrect estimation of the effects' accuracy. Also, the analyses reveal that the effects may have different accuracy levels and some effects (even those with large magnitude contributions) may be non-significantly different from zero. This implies that there are effects that are not relevant to the explanation of China's EEBT. Our results therefore suggest that not considering the net entry effect or not being aware of the effects' accuracy may lead to incorrect economic interpretations and misguided policy-making. Another interesting point arising from the methodology is that the complexity of S/S's approach, as the number of effects increases, should go hand in hand with the results' accuracy. Hence, from this standpoint, the S/S's approach should be preferred when the number of effects is high, contrary to what is stated in the literature.

JEL classification: C18, C43, P28, Q48, Q58.

Keywords: Decomposition analysis, Shapley (1953)/Sun (1998)'s approach, Bootstrapped confidence interval, Net entry effect, Effects' accuracy.

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1 Introduction

Index decomposition analysis (IDA thereafter), additive or multiplicative[1], is a commonly used method in the literature to capture the contributions of predefined effects on an aggregate, such as CO2 emissions, energy consumption and energy intensity (see Hoekstra and van den Bergh, 2003; Ang, 2004; Wang et al., 2017a). IDA has gained importance since its adoption in the 1970s by energy researchers to study the impact of structural change and sectoral energy intensity change on industrial energy use (Extensions have been made to study energy demand in other sectors, such as transport, residential, service and the economy as a whole).

Referring to Ang and Zhang (2000); Ang et al. (2003); Ang (2004) and Ang (2015); the use of IDA is no longer limited to the field of energy demand and supply. Since the environment has become a worldwide concern, IDA has emerged as a popular tool to investigate the factors that drive the change in energy-related gas emissions (see Ang and Zhang, 2000; Ang, 2015) and the change in trade-related gas emissions (see Outchiri and He, 2020). With the increasingly focus on sustainable development, IDA has turned out to be a useful analytical technique in the area of material flows and dematerialization in order to capture the relative contribution of each effect (such as resource use intensity) that influence the change in material use in an economy (see Ang et al., 2003; Ang, 2004). New areas of IDA application also include water use, non-energy use, food production etc. (see Ang, 2015). Several national agencies of countries like Canada, USA etc. and international agencies (such as International Energy Agency, World Bank etc.) have used this analysis technique to build energy efficiency appropriate indicators or indices in order to monitor national and worldwide trends in energy efficiency and to track progresses towards the energy efficiency targets (see Ang and Zhang, 2000; Ang et al., 2003; Ang, 2004; Ang et al., 2010; Ang, 2015). Furthermore, IDA has been used in the cross-country comparison analyses to measure the relative contribution of factors that drive differences in energy or environmental aggregates (such as energy consumption and intensity, carbon dioxide emissions and intensity, etc.) and also in other aggregates between two countries or regions (see Ang and Zhang, 2000; Zhang and Ang, 2001; Ang, 2004). Also, while traditionally this technique has been used mainly for retrospective analyses, studies are increasingly using it for prospective analyses (see Ang, 2015).

All in all, it is clear that IDA has been widely adopted in the literature of several fields, especially in the energy and environmental fields as an analytical technique that may help to understand the change in energy, environmental, economic and socio-economic aggregates for policy making at the sectoral, national and international level on different issues. As also mentioned by Ang et al. (2003), the review made by Ang and Zhang (2000) revealed that the majority of studies are oriented towards policy analysis at the sectoral, national or international level. Ang et al. (2003) also discussed the use of IDA in policy design at the national and international level.

IDA includes several approaches that can be grouped into Divisia index, Laspeyres index and others[2] (see Ang, 2004). Usually, the additive form of "Log Mean Divisia Index I" (LMDI I)

[1]The additive decomposition is done on the difference change in an aggregate (For example, CO2 emissions, trade-related emissions, energy consumption, energy intensity etc.), while the multiplicative one is done on its ratio change. For more details see for example Hoekstra and van den Bergh (2003); Ang (2004) and Wang et al. (2017a).

[2]The recommended Divisia Index-related approaches include: Log Mean Divisia Index I (LMDI I) and Arithmetic Mean Divisia Index (AMDI) in their additive and multiplicative forms. The recommended Laspeyres Index-related

and the Shapley (1953)/Sun (1998) (S/S thereafter) approaches are the additive decomposition approaches preferred or recommended in the literature (see Ang and Zhang, 2000; Ang, 2004, 2015). This preference is due to the fact that these approaches lead to decomposition without residue and present relatively easy computational challenges compared, for example, to Adaptive Perfect Decomposition (so-called mean rate-of-change index) (see Ang and Zhang, 2000; Ang et al., 2003; Ang, 2004). But LMDI I is more used than S/S, mainly because of the simplicity of its formulae. Indeed, the formulae of the S/S approach become more difficult as the number of effects increases, whereas those of the LMDI I approach remain invariant no matter how many effects are involved in the decomposition analysis (see Zhang and Ang, 2001; Ang et al., 2003; Ang, 2004). The concern is that these two additive decomposition approaches tend to provide different results (For example, see the results in Table 2 of Ang and Zhang (2000), Ang et al. (2003) and Ang (2004), those in Table 4 of Hoekstra and van den Bergh (2003) and those in Tables 2-4 of Zhang and Ang (2001)). This difference between the two decomposition approaches was pointed out by Zhang and Ang (2001). In general, Ang (2004) argued that the relative contributions of the effects are approach-dependent and therefore the choice of decomposition approach affects the decomposition analysis results. The same concern was raised by Hoekstra and van den Bergh (2003).

Such sensitivity of results to the approach may be problematic for several reasons. As documented above, IDA has increasingly gained prominence in several fields, and most decomposition studies are policy-oriented. In this respect, the decomposition analysis results (the sign and magnitude of the relative contributions of the effects) are tied to policy initiatives (see Wang et al., 2017a). Accordingly, this would imply that policy-making drawn from the decomposition analysis results could be approach-dependent. This is more troubling insofar as the decomposition analysis results are not supported by a statistic that indicates the accuracy of the results. Dietzenbacher and Los (1998) (DL thereafter) advocated to report results when using their approach (which can be considered to be identical to that of S/S[3]) with statistics (the range relative to the average and the coefficient of variation) that allow to assess the dispersion around the average relative contributions of the effects. Hoekstra and van den Bergh (2003) stated that the minimum and maximum relative contributions of each effect obtained from DL's approach can be useful to indicate the range of possible relative contributions of each effect. Although these guidelines may be helpful in the results analysis and policy implications, we will remain uncertain about whether the results are accurate or not, at least if they are statistically significant (i.e. significantly different from zero) at standard significance levels (1%, 5% and 10%).

approaches include: "Modified Fishers Ideal Index" (MFII), "Conventional Fisher Ideal Index" (CFII) for multiplicative decomposition; and Shapley/Sun, Marshall-Edgeworth for additive decomposition. Other approaches include: Conventional Laspeyres Index (CLI), Adaptive Weighting Parametric Divisia Index (AWPDI), Adaptive Perfect Decomposition (APD), "Log Mean Divisia Index II" (LMDI II). This categorization was done by Ang (2004). Interested readers can refer to Ang (2004) for methodological details of these approaches. Ang (2015) detailed the LMDI I and II approaches and their differences.

[3]According to DL, when the number of effects is n, there are $n!$ possible alternative decompositions (they are complete decompositions) that depend on the order in which the decomposition effects are introduced into the analysis. They showed that there is a significant variation in the results depending on the alternative decomposition chosen and it can seriously affect the economic interpretation of the results. They proposed to take the average of all the alternative decompositions and to report the average relative contribution of each effect along with the range relative to the average as well as the coefficient of variation. In doing so, it appears that this approach is identical to that of S/S, because the average relative contribution of each effect obtained using DL's approach are identical to the relative contribution of each effect obtained when using S/S's approach (see Hoekstra and van den Bergh, 2003). Therefore, the decomposition results obtained with S/S's approach can be interpreted as the average decomposition results when applying DL's approach. So when we use the acronym S/S to refer to the Shapley (1953)/Sun (1998)'s approach, it can also refer to the DL's approach.

This paper, building on the previous work of Albrecht et al. (2002) (who first introduced Shapley (1953)'s approach in IDA), Sun (1998) and Dietzenbacher and Los (1998), then proposes to estimate the standard errors (or confidence intervals) of each average relative contribution in order to investigate whether or not each effect is significantly different from zero at the standard significance levels. To do so, we use the same statistics (the range relative to the average and the coefficient of variation) as in DL to illustrate that there is substantial variability (created by the $n!$ alternative decompositions) around the average relative contribution of each effect. We therefore use this variability to test the accuracy of the relative contribution of each effect obtained through the S/S's approach. In order to estimate the standard errors required to perform this test, we propose to use the bootstrapped normal-approximation confidence interval, given that the number of observations (with n effects, we will have $n!$ observations) is finite. This is based on a weak assumption that the estimated distribution of each effect is approximately normal. We discuss this assumption and we conclude that it is approximately true, which is sufficient when estimating standard errors. By doing so, we are able to estimate the statistical significance of each effect at different standard significance levels. As in an additive decomposition, the interpretation of a relative contribution always involves comparing it to zero with respect to its sign and magnitude, so the interpretation of statistical significance is the same as that of a coefficient obtained in standard econometric analysis. As a result, we should now be able to find out whether the relative contribution of each effect is significantly different from zero at standard significance levels, meaning whether or not each effect matters in explaining the phenomenon (i.e. the change in the aggregate) under study.

We address another concern that could lead to erroneous results if not properly handled. To illustrate this, let's use our application example. In application, we decompose the CO2 emissions embodied in the bilateral trade (EEBT) between China and its partners. Indeed, with increasingly disaggregated databases, particularly at the product level (our database contains 1033 products, traded between China and its 181 partners from 1995 to 2014), it is possible that in a given year a country may exchange a new product (product entry) or no longer exchange a given product (product exit). This movement (entry and/or exit) of products isn't considered by standard decomposition approaches, in particular that of S/S. However, this yields other effects, namely the entry effect and the exit effect (the difference between them gives the net entry effect), which should be accounted for in order to properly estimate both the relative contribution of the other effects and their statistical significance[4]. As mentioned by Barrows and Ollivier (2016), taking this effect into account remains a challenge.

Our paper contributes to the literature on decomposition analysis in several respects. One of the previous criticisms of decomposition analyses was related to the challenge imposed by the residual part, which is often very high and difficult to interpret (see Sun, 1998). This problem has been solved by proposing decomposition approaches that are residue-free, such as the S/S and LMDI I approaches. This introduced the notion of perfect decomposition, and it has become a criterion for the choice of decomposition approach known as factor-reversal

[4]Based on Barrows and Ollivier (2016) and Cherniwchan et al. (2017), ignoring the net entry effect could lead to a poor estimate of relative contributions and would also complicate the interpretation of the results. In this study, we argue that, in addition, ignoring the net entry effect could have an impact on the estimation of the statistical significance of the effects.

test (which implies that the approach provides a residue-free decomposition)(see Ang, 2004). Along this methodological improvement route, our work raises another criticism of decomposition analyses and proposes a first solution. Our critique relies on a crucial drawback, stemming from the fact that the decomposition analysis results tend to be approach-dependent, which could make them unreliable. Even if efforts have been made to propose perfect decompositions, this does not solve the problem we raise here. However, knowing whether results are accurate or not helps to strengthen their reliability. Since most decomposition studies are policy-oriented, particularly in the energy and environmental fields, analysts and decision-makers would benefit from being aware of their results' accuracy and reliability when interpreting them for better policy-making. As a result, more accurate results will help researchers and policy makers to feel more confident with their economic interpretations and policy-making. Therefore, our work extends the criteria for the choice (see the review in next section or Ang (2004)) of the decomposition approach by introducing a significance test of each effect, which we refer to accuracy criterion.

It emerges from our results that omitting the net entry effect can lead to under- or over-estimates of the contributions, wrong signs and even a wrong order of magnitude of the contributions, and incorrect estimation of the effects' accuracy. Also, significance tests reveal that the effects may have different accuracy levels and some effects (even those with large magnitude contributions) may be non-statistically significant at standard levels. This implies that there are effects (obviously those that are not significantly different from zero) that are not relevant to the explanation of China's EEBT. Our results therefore suggest that not considering the net entry effect or not being aware of the effects' accuracy may lead to incorrect economic interpretations and misguided policy-making. An interesting point arising from the methodology is that from the standpoint of the results' accuracy, the S/S's approach should be preferred when the number of effects is high (as it should improve the results' accuracy), contrary to what is stated in the literature.

The rest of our paper is set out in six sections. Section 2 presents a brief review comparing, on the one hand, the IDA and the structural decomposition analysis (SDA thereafter), and on the other hand the LMDI and S/S approaches. Section 3 describes the application case, while Section 4 reviews the decomposition approaches. Section 5 deals with the methodology adopted in order to perform the significance test for each effect. Section 6 reports the results and analyses, and Section 7 concludes the study.

2 Brief comparative review

2.1 IDA versus SDA

To analyze and understand historical changes in environmental and socio-economic indicators, it's useful to show the drivers that influence changes in these indicators (Hoekstra and van den Bergh, 2003). Structural decomposition analysis (SDA) and index decomposition analysis (IDA) are two techniques[5] for decomposing changes in an indicator (Hoekstra and van den Bergh, 2003; Wang

[5]For a review of the literature and methodology on SDA, the reader can consult for example Hoekstra and van den Bergh (2003); Su and Ang (2012) and Wang et al. (2017a). For the IDA, the reader can consult, for example Ang and Zhang (2000); Hoekstra and van den Bergh (2003); Ang (2004); Su and Ang (2012); Xu and Ang (2013); Ang (2015) and Wang et al. (2017a). For a comparison of the two, the reader can refer to Hoekstra and van den Bergh (2003); Su and Ang (2012) and Wang et al. (2017a).

et al., 2017a). Their objective is to isolate the contributions of predefined determinants on an aggregate, and they allow a better understanding of energy-related and emissions-related themes (Wang et al., 2017a).

SDA uses information from an input-output table (IOT) and can combine it with data at the sectoral level, while IDA only uses data at the sectoral level (see Hoekstra and van den Bergh, 2003; Levinson, 2009; Wang et al., 2017a). Sectoral data exist by year over long series and for a large number of countries, which isn't the case for reliable IOT. The later has only recently become available on an annual basis for a few countries. Thus, IDA has the advantage of requiring little information and this information is relatively abundant, which makes it possible to carry out more detailed time-series analyses than SDA (see Hoekstra and van den Bergh, 2003). In addition, SDA may exhibit some biases related to the low sectoral disaggregation of IOT[6]. However, SDA allows more detail in the decomposition of the economic structure by distinguishing more technological effects and final demand effects (see Hoekstra and van den Bergh, 2003). Also, SDA captures the direct and indirect effects of demand (while IDA captures only direct effects), because SDA uses the input-output analysis framework that takes into account indirect effects through Leontief's inverse (see Wang et al., 2017a; Hoekstra and van den Bergh, 2003).

Regarding methodology and application, there are similarities and differences between the two techniques (Wang et al., 2017a). Wang et al. (2017b) present the links between them. IDA technique can find their equivalence in SDA and vice versa, but as said above they offer different decomposition effects (see Hoekstra and van den Bergh, 2003; Su and Ang, 2012; Wang et al., 2017a). Indeed, for example, both can capture the scale effect of production (measuring the effect of total output) and the intensity effect (the technological effect that captures at the sector level the change in energy use per unit of output) (Hoekstra and van den Bergh, 2003). In addition, SDA can capture the Leontief effect (another technological effect measuring change in the structure of intermediate consumption) and the final demand effect (capturing the change in demand for products in each sector), while IDA can capture the structure effect (measuring the change in the share of production) (see Hoekstra and van den Bergh, 2003). By establishing conceptual links between the two in terms of modeling, Wang et al. (2017a) show that their main difference lies in the way they model the economic structure effect, which means a difference in their methodological foundation. Beyond their difference, the choice between the two depends on the study objective, the user's interest and the type of data available (Wang et al., 2017a). However, in terms of application, SDA is more specific, more restrictive and narrower, while ADI is more complete, simpler and more flexible to model, and easier to use and apply (Wang et al., 2017a). For these reasons, we will use the IDA framework to illustrate our proposal. However, this proposal can also be very well applied in the context of additive SDA with the S/S's approach (or DL's approach).

[6]Some scholars investigated the sensitivity of the results to sectoral aggregation. Wyckoff and Roop (1994) show that with aggregation, CO2 emissions from manufactured imports are about 30% lower. Jacobsen (2000) shows that in the case of 117 industries in 1992, energy demand is about 7% higher than in a situation with no change in structure and trade balance, while with 27 sectors this energy demand is 19% higher. Lenzen et al. (2004) show that in the case of a Multi-Regional Input-Output, aggregation leads to an increase in the deficit of CO2 incorporated into trade of 0.3 to 3.3 Mt 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. However, Lenzen (2011) studies the opposite case and concludes that the alternative of disaggregating input-output data to match the classification of environmental data is preferable to aggregating environmental data. So sectoral aggregation has a significant impact on results and is likely to generate significant errors (Lenzen et al., 2004).

2.2 LMDI I versus S/S

The most popular IDA approaches can be grouped under two headings: those related to the Divisia index (change in logarithm) and those related to the Laspeyres index (percentage change) (Ang, 2004). The Divisia index-related approaches capture the contribution of each effect by the weighted sum of logarithmic growth rates at the entity or sub-aggregate level, while the Laspeyres index-related approaches measure the contribution of each effect by changing only the value of an effect from year 0 to T each time and assigning certain values to all other effects that depend on the specification of the integral path (Wang et al., 2017a). Ang (2004) proposed four criteria (theoretical foundation, adaptability, ease of use and ease of result interpretation)[7] that can enable us to make a less subjective choice between the different IDA approaches. To evaluate the theoretical foundation of an IDA approach, four tests of index number theory[8] are used, namely the factor-reversal, time-reversal, proportionality and aggregation tests[9] (Ang, 2004). The factor-reversal test is the most important and the approaches that pass it are highly desirable (they are recognized as perfect decompositions), because they leave no residue (Ang, 2004). Based on this test, Ang (2004) recommends four IDA approaches that include two Divisia index-related approaches (LMDI I in its multiplicative and additive form)[10] and two other Laspeyres index-related approaches (Modified Fishers ideal index (MFII) multiplicative form[11] and S/S additive form). Therefore, in an additive IDA, as in this study, the choice is between LMDI I in its additive form, introduced by Ang et al. (1998) and the S/S's approach.

The application of LMDI is complicated when data can be zero or negative because of logarithmic weights. Ang and Choi (1997) showed that the results will converge if we replace zeros with small positive values. Ang et al. (1998) presented an alternative to Ang and Choi (1997) by identifying eight cases in which zero values are possible and they propose limit values for each of these cases. Ang (2004) recommends the Ang and Choi (1997) technique, but Wood and Lenzen (2006) showed that this technique is not necessarily robust and can lead to significant errors if the data contain a large number of zeros and/or small values. According to Ang and Liu (2007a), the technique of Ang et al. (1998) is theoretically better, but non-specialists should use that of Ang and Choi (1997). The solutions are more complex in the case of negative data and require careful data processing (see Ang and Liu, 2007b). Ang (2004) recommends that in the case of negative data, the Laspeyres index-related approaches should be used. This means that in the case of additive decomposition, the S/S method should be preferred.

[7] The theoretical foundation is based on four tests of index number theory (explained below). Adaptability refers to whether a method is able to manage data with large variations, zero values, or negative values. Ease of use refers to the ease of the application of the method to different problems. The ease of result interpretation is related to the theoretical foundation and the possible links between its additive form and multiplicative form. For more explanations, please refer to Ang (2004).

[8] Please see Fengling (2005) for an explanation of this theory.

[9] The factor-reversal test implies that the approach provides a residue-free decomposition and therefore perfect decomposition analysis. The time-reversal test means that there is a simple reciprocal relationship between the effect's contribution of a decomposition from 0 to T and that of a decomposition from T to 0. In the case of additive decomposition, this means that the effect's contribution obtained from a decomposition from 0 to T must be equivalent to the opposite of the one obtained from a decomposition from T to 0. The proportionality test means that if, for example, we multiply the CO2 emission intensities by a positive constant number m, the new contribution of the effect (for example technique effect) will be multiplied by m. The aggregation test means that there is an aggregation relationship that allows a contribution of the effect calculated, for example, in the OECD sub-sample to be aggregated to that calculated in the non-OECD sub-sample, so that the result of this aggregation is equivalent to the contribution of the effect calculated with the whole sample.

[10] The reader can find all the variants of LMDI in Ang (2015).

[11] Known as the "Generalized Fisher Index" for more than two effects (see Ang et al., 2004).

The S/S's approach is robust to zero and negative values without data transformation. This approach based on Shapley's value doesn't require any hypothesis to provide a perfect decomposition (Albrecht et al., 2002). This particularity of S/S's approach provides a very high degree of adaptability relative to the others. Its additive form instead of multiplicative, and also the fact that it's residue-free makes it easier to interpret its results. Because additive decompositions facilitate interpretation for non-experts (Hoekstra and van den Bergh, 2003) and the presence of residues causes interpretation problems (Albrecht et al., 2002). Also, an additive decomposition analysis for a total aggregate is easier to present, explain and understand (Wang et al., 2017a). All these characteristics make it easy to use, as it can be applied to several issues related to decomposition analysis. The Shapley's decomposition approach is symmetrical, i.e. the treatment of the effects is impartial, without making any other theoretical assumptions and allows very complex decompositions (Albrecht et al., 2002). Based on Ang and Zhang (2000); Albrecht et al. (2002); Hoekstra and van den Bergh (2003); Ang et al. (2003); Ang (2004) and Fengling (2005) we can summarize the S/S's approach theoretical foundation properties as follows: perfect by construction and therefore checks the factor-reversal test, checks the time-reversal test, checks the proportionality test and doesn't check the aggregation tests[12]. Thus, among the criteria for the choice of a decomposition approach, the S/S's approach verifies all these criteria, except for the aggregation criterion. There isn't a decomposition approach that can verify all the criteria (Hoekstra and van den Bergh, 2003; Fengling, 2005), as it has been shown that it's mathematically impossible for some properties of index number theory to be simultaneously respected by a single index (Hoekstra and van den Bergh, 2003). Hence, the most appropriate approach is usually chosen according to the data and the objectives of the study (Ang and Zhang, 2000; Fengling, 2005).

Despite its advantages, S/S formulae become more complex as the number of effects increases, whereas those of LMDI I are invariant to the number of effects (Ang, 2004). This complexity is most noticeable when the decomposition effects exceed three (3), which is increasingly the case in studies (Ang and Zhang, 2000; Ang, 2004). Especially with very disaggregated data, it is very likely that decomposition analyses will go beyond the standard framework (scale effect, composition effect and technical effect). However, this complexity can be considered as an advantage if we exploit it properly. This is what we are trying to do in this paper.

3 An application case of decomposition analysis

3.1 CO2 emissions embodied in bilateral trade (EEBT)

To present Shapley's value approach, Sun's approach and Dietzenbacher and Los's approach, we consider the example of an IDA of CO2 emissions embodied in China's bilateral trade (EEBT). Indeed, IDA is increasingly used to capture the determinants of EEBT (see Dong et al., 2010; Wu et al., 2016; Outchiri and He, 2020). We decompose the change in EEBT into several determinants (effects). The decomposition strategy presented here is taken from Outchiri and He (2020), thus readers interested in the details can consult this paper.

[12]LMDI I additive form verifies the theoretical foundation properties except for the proportionality test (Ang et al., 2009). But it is not robust to non-positive values unless the data are transformed as discussed above.

Let:

$$EEBT_{ct} = \sum_{f} \sum_{p} \left[\varphi_{cpt} X^{f}_{cpt} - \varphi_{fpt} M^{f}_{cpt} \right] \tag{1}$$

The indices c, f, p and t represent respectively China, China's trading partners, product and time. The φ_{cpt} (φ_{fpt}) are the emission intensities of country c (f), for product p, at time t. The X^{f}_{cpt} (M^{f}_{cpt}) represent the exports (imports) of China to (from) its partner f of product p at time t. Based on He and Jacquemin (2016), equation 1 becomes :

$$EEBT_{ct} = \underbrace{\sum_{f} \sum_{p} \left[\varphi_{cpt} - \varphi_{fpt} \right] X^{f}_{cpt}}_{Creations_{ct}} + \underbrace{\sum_{f} \sum_{p} \varphi_{fpt} \left[X^{f}_{cpt} - M^{f}_{cpt} \right]}_{Transfers_{ct}} \tag{2}$$

$Creations_{ct}$ and $Transfers_{ct}$ represent respectively the new emission creations and the real emission transfers. The new emission creations are also known in the literature as the impact of Chinese exports on global CO2 emissions (see Ding et al., 2018). The $Creations_{ct}$ represent the part of China's EEBT due to the difference between its CO2 emission intensities and those of its partners and the size of exported products. While, the $Transfers_{ct}$ refer to the part of China's EEBT due to China's trade imbalances and technical efficiency of its partners. If the $Creations_{ct}$ are positive, then China's exports to its trading partners create new emissions (China's exports increase global CO2 emissions) and vice versa. A positive $Transfers_{ct}$ means that there is a transfer of emissions from the partners to China and vice versa.

Three reasons led us to prefer this strategy instead of the standard strategy, widely used in the literature (see Xu and Dietzenbacher, 2014), that separates the EEBT into its two direct components, namely the emissions embodied in exports (EEE) and the emissions embodied in imports (EEI). First, as Outchiri and He (2020) mentioned, splitting the EEBT into $Creations_{ct}$ and $Transfers_{ct}$ and examine them afterwards helps to better understand the role of trade in environmental issues. Indeed, this strategy helps to address environmental challenges raised by international trade. One of the challenges is that international trade can allow the transfer of emissions from one country to another through trade of products. This is captured by real emission transfers, which reflect the fact that trading partners can take advantage of international trade to reduce their emissions by transferring them to other countries through trade imbalances (in some strategic products). Referring to the pollution haven hypothesis (PHH), another challenge is that international trade can lead to a shift of dirty production towards developing countries because the latter have less strict environmental regulations than developed countries (see Grossman and Krueger, 1991; Antweiler et al., 2001; Copeland and Taylor, 2004). Therefore, since it is assumed that developing countries have higher emission intensities on average than developed countries, this relocation of dirty production should increase international trade-related emissions, especially in developing countries. Hence, this depends on the difference in emission intensities of relocated products between developed and developing countries and the extent of relocation. This part of the EEBT is so-called new emission creations, and it depends on the size of China's exports and the technical gap between China and its partners.

Secondly, the strategy adopted enables to know whether a country (here China) is increasingly exporting products in which it has an environmental disadvantage (relative high emission intensities) or not. Whereas, the standard strategy only allows to know whether the country is increasingly exporting dirty products or not. Assuming that international trade is driven by comparative advantage, then the strategy adopted here is more suitable for analyzing the issues raised by international trade-related emissions by contributing to the discussion on PHH.

Thirdly, as we can remark it is possible to have non-positive values because of the difference in emission intensities between China and its partners and trade imbalances. So as discussed above, the S/S's approach is more suitable than LMDI's approach because the S/S's approach is robust to zero and negative values without data transformation. Given that our paper focuses on the S/S's approach, such an example is well fitted to highlight the relevance of this decomposition approach.

3.2 The net entry effect

When we consider two years, we have three types of products[13]: the set of existing and entering products traded and the set of exiting products that are no longer traded between China and its partners. Thus, the variation of EEBT can be written as:

$$\Delta EEBT_{ct} = \Delta Creations_{ct}^{Ex} + \Delta Transfers_{ct}^{Ex} + \underbrace{\left[EEBT_{ct}^{En} - EEBT_{ct}^{So}\right]}_{NEE} \tag{3}$$

Where Ex, En and So refer respectively to the set of existing, entering and exiting products. $\left[EEBT_{ct}^{En}\right]$ refers to EEBT due to new products traded between China and its partners, and $\left[EEBT_{ct}^{So}\right]$ represents EEBT due to products that are no longer traded between China and its partners. A positive (negative) entry effect signifies that the new products traded contribute to increase (decrease) EEBT, while a positive (negative) exit effect means that products that are no longer traded help to decrease (increase) EEBT. The difference $\left[EEBT_{ct}^{En} - EEBT_{ct}^{So}\right]$ is the net entry effect (NEE). A positive (negative) net entry effect (NEE) means that the movements in and out of traded products contribute to increase (decrease) EEBT. However, the full interpretation of the net entry effect is based on the sign of entry effect and that of exit effect. For example, if the net entry effect is positive with a positive entry effect and a positive exit effect then this means that emissions generated by trading new products exceed emission reductions obtained by no longer trading some products. We argued that failure to account for the net entry effect could lead to bias when assessing the contributions of other effects.

3.3 Drivers of changes in new creations and real transfers

$Creations_{ct}^{Ex}$ and $Transfers_{ct}^{Ex}$ are expressed as in equation (1). We can rewrite them, by focusing only on existing products, as follows :

[13] Existing products mean products that are exchanged in both years. Entering products mean products that are exchanged only in the current year (new products traded) and exiting products mean products which are exchanged only in the previous year (base or reference year).

$$Creations_{ct}^{Ex} = \sum_{f} \sum_{p \in Ex} \underbrace{X_{ct}}_{E_{ct}} \times \underbrace{(\frac{X_{ct}^{f}}{X_{ct}})}_{C1_{ct}^{f}} \times \underbrace{(\frac{X_{cpt}^{f}}{X_{ct}^{f}})}_{C2_{cpt}^{f}} \times \underbrace{(\varphi_{cpt} - \varphi_{fpt})}_{T_{cpt}^{f}} \tag{4}$$

$$Transfers_{ct}^{Ex} = \sum_{f} \sum_{p \in Ex} \underbrace{(X_{ct} - M_{ct})}_{E_{ct}} \times \underbrace{(\frac{X_{ct}^{f} - M_{ct}^{f}}{X_{ct} - M_{ct}})}_{C1_{ct}^{f}} \times \underbrace{(\frac{X_{cpt}^{f} - M_{cpt}^{f}}{X_{ct}^{f} - M_{ct}^{f}})}_{C2_{cpt}^{f}} \times \underbrace{\varphi_{fpt}}_{T_{cpt}^{f}} \tag{5}$$

The first two right terms of equation 3 are respectively variations of equations 4 and 5. The changes in $Creations_{ct}^{Ex}$ (see equation 4) can be influenced by four effects: scale effect of exports (E_{ct}), between-partner composition effect of exports ($C1_{ct}^{f}$), within-partner (between-product) composition effect of exports ($C2_{cpt}^{f}$) and technical gap effect (T_{cpt}^{f}). Also, the $Transfers_{ct}^{Ex}$ (see equation 5) can be explained by scale effect of net exports (E_{ct}), between-partner composition effect of net exports ($C1_{ct}^{f}$), within-partner (between-product) composition effect of net exports ($C2_{cpt}^{f}$) and a technical effect of partner (T_{cpt}^{f}). Indeed, scale effect captures the impact of China's total exports (net exports) on EEBT, between-partner composition effect indicates whether or not China's trade is further shifted towards partners with relative high emission intensities, within-partner (between-product) composition effect captures the fact that China's trade is further shifted towards clean or dirty products (also provides information on whether or not China is exporting products in which it has an environmental disadvantage), technical gap effect captures the impact of the difference in emission intensities between China and its partners, and technical effect of partner isolates the impact of changes in emission intensities of partners[14]. Thus, equations 4 and 5 can be rewritten more compactly as follows:

$$I_{ct}^{Ex} = \sum_{f} \sum_{p \in Ex} E_{ct} \times C1_{ct}^{f} \times C2_{cpt}^{f} \times T_{cpt}^{f} \tag{6}$$

Where $I = \{Creations, Transfers\}$. The expressions of the four effects (drivers) are defined as above in equations 4 and 5 depending on $I = \{Creations, Transfers\}$.

4 Shapley/Sun's decomposition approach

4.1 Contribution of each effect

The aim is to isolate the contribution of each effect (driver) in equation 6 depending on $I = \{Creations, Transfers\}$. After applying the decomposition strategy to equation 6, we will obtain the following relationship :

$$\Delta I_{ct}^{Ex} = \Delta I\_E_{ct} + \Delta I\_C1_{ct} + \Delta I\_C2_{ct} + \Delta I\_T_{ct} \tag{7}$$

ΔI_E_{ct}, ΔI_C1_{ct}, ΔI_C2_{ct} and ΔI_T_{ct} represent the contribution of E_{ct}, $C1_{ct}^{f}$, $C2_{cpt}^{f}$ and T_{cpt}^{f} depending on $I = \{Creations, Transfers\}$. Equation 7 completes equation 3 by providing the expressions of $Creations_{ct}^{Ex}$ and $Transfers_{ct}^{Ex}$. To estimate the contributions in equation 7, we

[14]Since the purpose of this paper is not the interpretation of these different effects, but rather how to properly capture the contributions of these effects, we do not go into the details regarding what each effect means. To find out more about these different effects, we refer readers to Outchiri and He (2020).

present the Sun's approach, the Shapley's value approach and the Dietzenbacher and Los's approach for additive decomposition.

4.2 Sun's approach

Sun's approach is also known as the refined Laspeyres index (see Ang and Zhang, 2000). This approach has solved the residue treatment problem faced by most ex-ante decomposition studies. Some studies have omitted the residue, introducing a significant estimation error and others call it the interaction effect which leaves the reader with a new puzzle (Sun, 1998). Based on the Laspeyres index we will have:

$$\Delta I\_E_{ct} = \sum_f \sum_{p \in Ex} \Delta E_{ct} C1^f_{c0} C2^f_{cp0} T^f_{cp0} \tag{8}$$

$$\Delta I\_C1_{ct} = \sum_f \sum_{p \in Ex} E_{c0} \Delta C1^f_{ct} C2^f_{cp0} T^f_{cp0} \tag{9}$$

$$\Delta I\_C2_{ct} = \sum_f \sum_{p \in Ex} E_{c0} C1^f_{c0} \Delta C2^f_{cpt} T^f_{cp0} \tag{10}$$

$$\Delta I\_T_{ct} = \sum_f \sum_{p \in Ex} E_{c0} C1^f_{c0} C2^f_{cp0} \Delta T^f_{cpt} \tag{11}$$

Referring to equation 7 and equations 8 to 11, this decomposition will not be perfect, because it leaves the following residue:

$$\begin{aligned} Residue_T &= \Delta I^{Ex}_{ct} - [\Delta I\_E_{ct} + \Delta I\_C1_{ct} + \Delta I\_C2_{ct} + \Delta I\_T_{ct}] \\ &= \sum_f \sum_{p \in Ex} (\Delta E_{ct} \Delta C1^f_{ct} C2^f_{cp0} T^f_{cp0} + \Delta E_{ct} C1^f_{c0} \Delta C2^f_{cpt} T^f_{cp0} \\ &\quad + \Delta E_{ct} C1^f_{c0} C2^f_{cp0} \Delta T^f_{cpt} + E_{c0} \Delta C1^f_{ct} \Delta C2^f_{cpt} T^f_{cp0} + E_{c0} \Delta C1^f_{c1} C2^f_{cp0} \Delta T^f_{cpt} \\ &\quad + E_{c0} C1^f_{c0} \Delta C2^f_{cpt} \Delta T^f_{cpt} + \Delta E_{ct} \Delta C1^f_{ct} \Delta C2^f_{cpt} T^f_{cp0} + \Delta E_{ct} \Delta C1^f_{c1} C2^f_{cp0} \Delta T^f_{cpt} \\ &\quad + \Delta E_{ct} C1^f_{c0} \Delta C2^f_{cpt} \Delta T^f_{cpt} + E_{c0} \Delta C1^f_{ct} \Delta C2^f_{cpt} \Delta T^f_{cpt} \\ &\quad + \Delta E_{ct} \Delta C1^f_{ct} \Delta C2^f_{cpt} \Delta T^f_{cpt}) \end{aligned} \tag{12}$$

To achieve perfect decomposition, Sun (1998) proposes to distribute this residue according to the principle of "jointly created and equitably distributed". For example, the first right term in equation 12 was "jointly created" by the effects E_{ct} and $C1^f_{ct}$, because they are the ones that vary while the others are constant. Consequently, this term will be "equitably distributed" between the contributions of the two effects, thus added to equation 8 and 9. By applying this principle to all the other right-hand terms of equation 12, we will obtain the versions of equations 8 to 11 that lead to a perfect decomposition. Equation 13 below is the version of equation 8, which allows a perfect decomposition. This equation gives the contribution of scale effect of exports (or net exports). The approach is symmetrical, then the other equations can be deduced from equation 13.

$$\Delta I\_E_{ct} = \frac{1}{24}\sum_{f}\sum_{p\in Ex}(6\times\Delta E_{ct}C1^{f}_{c0}C2^{f}_{cp0}T^{f}_{cp0} + 2\times\Delta E_{ct}C1^{f}_{ct}C2^{f}_{cp0}T^{f}_{cp0}$$
$$+ 2\times\Delta E_{ct}C1^{f}_{c0}C2^{f}_{cpt}T^{f}_{cp0} + 2\times\Delta E_{ct}C1^{f}_{c0}C2^{f}_{cp0}T^{f}_{cpt} + 2\times\Delta E_{ct}C1^{f}_{ct}C2^{f}_{cpt}T^{f}_{cp0}$$
$$+ 2\times\Delta E_{ct}C1^{f}_{c0}C2^{f}_{cpt}T^{f}_{cpt} + 2\times\Delta E_{ct}C1^{f}_{ct}C2^{f}_{cp0}T^{f}_{cpt} + 6\times\Delta E_{ct}C1^{f}_{ct}C2^{f}_{cpt}T^{f}_{cpt}) \quad (13)$$

Sun (1998) provided a general formula for n-effects. The assumption is that there's no reason to do otherwise, even if the validity of this principle isn't proven (Albrecht et al., 2002). This limitation of Sun's principle has led Albrecht et al. (2002) to introduce an IDA approach which is perfect by construction based on Shapley's value.

4.3 Shapley's value approach

Shapley (1953), based on three axioms (symmetry, nullity and additivity)[15], proposes a unique solution (the Shapley's value) to the problem of distribution of gains among players in a cooperative game (with possibility of coalition) with transferable utility. The Shapley's value gives the real power of any player, and in the case of a decomposition analysis this value gives the real contribution of each effect. The idea, in the case of n players (effects in the case of an IDA), is to make $n!$ calculations of the contributions of each player depending on the order in which the players are introduced into the calculations and to take the average of these contributions at the level of each player. This yields the average contribution of each player (effect in the case of an ADI). Thus, the Shapley's value is independent of the order in which the effects are introduced into the analysis and also leaves no residue by construction (Albrecht et al., 2002). Albrecht et al. (2002) are the first to mention the similarities between the problem of cooperative game theory and the one addressed by decomposition analysis. They apply the Shapley's value approach for a perfect decomposition of carbon emissions.

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

$$\Delta I\_E_{ct} = \sum_{s=1}^{4}\frac{(s-1)!(4-s)!}{4!}\sum_{S:E_{ct}\in S;|S|=s}\left[I^{Ex}_{ct}(S) - I^{Ex}_{ct}(S-E_{ct})\right] \quad (14)$$

Where $I^{Ex}_{ct}(S)$ refers to the function as defined in equation 6, in which the elements of S (so-called the possible coalitions of E_{ct}) use only the data from period t, i.e. the current year. While all other elements use data from year 0, i.e. the base or reference year (in our case, 1995 is the reference year). We have eight (8) possible definitions of S :

$$S = \left\{ \begin{array}{l} (E_{ct}), (E_{ct}, C1^{f}_{ct}), (E_{ct}, C2^{f}_{cpt}), (E_{ct}, T^{f}_{cpt}), (E_{ct}, C1^{f}_{ct}, C2^{f}_{cpt}), \\ (E_{ct}, C1^{f}_{ct}, T^{f}_{cpt}), (E_{ct}, C2^{f}_{cpt}, T^{f}_{cpt}), (E_{ct}, C1^{f}_{ct}, C2^{f}_{cpt}, T^{f}_{cpt}) \end{array} \right\}$$

Thus, equation (14) becomes :

[15]Symmetry means that each effect must be treated symmetrically, nullity imposes a zero contribution to effects that don't contribute to any coalition, and additivity means that the contributions obtained from each coalition can be summed to obtain the total contribution of an effect.

$$\Delta I\_E_{ct} = \begin{cases} \frac{1}{4}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{c0} C2^f_{cp0} T^f_{cp0} & \text{If } S = (E_{ct}) \\ \frac{1}{12}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{ct} C2^f_{cp0} T^f_{cp0} & \text{If } S = (E_{ct}, C1^f_{ct}) \\ \frac{1}{12}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{c0} C2^f_{cpt} T^f_{cp0} & \text{If } S = (E_{ct}, C2^f_{cpt}) \\ \frac{1}{12}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{c0} C2^f_{cp0} T^f_{cpt} & \text{If } S = (E_{ct}, T^f_{cpt}) \\ \frac{1}{12}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{ct} C2^f_{cpt} T^f_{cp0} & \text{If } S = (E_{ct}, C1^f_{ct}, C2^f_{cpt}) \\ \frac{1}{12}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{ct} C2^f_{cp0} T^f_{cpt} & \text{If } S = (E_{ct}, C1^f_{ct}, T^f_{cpt}) \\ \frac{1}{12}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{c0} C2^f_{cpt} T^f_{cpt} & \text{If } S = (E_{ct}, C2^f_{ct}, T^f_{cpt}) \\ \frac{1}{4}\sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{ct} C2^f_{cpt} T^f_{cpt} & \text{If } S = (E_{ct}, C1^f_{ct}, C2^f_{ct}, T^f_{cpt}) \end{cases} \tag{15}$$

With the additivity property, we can sum the eight (8) elements of the equation 15. After a few manipulations, the result is identical to equation 13. The symmetry property allows us to derive the contributions of other effects in the same way or directly from equation 13. Since the sum of the contributions of the effects is equal to the decomposed aggregate (see equation 7), then the decomposition will be perfect by construction.

4.4 Dietzenbacher and Los's approach

Dietzenbacher and Los (1998) proposed an additive SDA approach, and Hoekstra and van den Bergh (2003) proposed an implementation of the latter in IDA. From equation 6, an additive decomposition analysis of changes in EEBT can be obtained as follows:

$$\begin{aligned}
\Delta I^{Ex}_{ct} &= \sum_f \sum_{p\in Ex} (E_{ct} C1^f_{ct} C2^f_{cpt} T^f_{cpt} - E_{c0} C1^f_{c0} C2^f_{cp0} T^f_{cp0}) \\
&= \sum_f \sum_{p\in Ex} (\Delta E_{ct} C1^f_{ct} C2^f_{cpt} T^f_{cpt} + E_{c0} C1^f_{ct} C2^f_{cpt} T^f_{cpt} - E_{c0} C1^f_{c0} C2^f_{cp0} T^f_{cp0}) \\
&= \sum_f \sum_{p\in Ex} (\Delta E_{ct} C1^f_{ct} C2^f_{cpt} T^f_{cpt} + E_{c0} \Delta C1^f_{ct} C2^f_{cpt} T^f_{cpt} + E_{c0} C1^f_{c0} C2^f_{cp1} T^f_{cp1} \\
&\quad - E_{c0} C1^f_{c0} C2^f_{cp0} T^f_{cp0}) \\
&= \sum_f \sum_{p\in Ex} (\Delta E_{ct} C1^f_{ct} C2^f_{cpt} T^f_{cpt} + E_{c0} \Delta C1^f_{ct} C2^f_{cpt} T^f_{cpt} + E_{c0} C1^f_{c0} \Delta C2^f_{cp1} T^f_{cp1} \\
&\quad + E_{c0} C1^f_{c0} C2^f_{cp0} T^f_{cpt} - E_{c0} C1^f_{c0} C2^f_{cp0} T^f_{cp0}) \\
&= \sum_f \sum_{p\in Ex} \Delta E_{ct} C1^f_{ct} C2^f_{cpt} T^f_{cpt} + \sum_f \sum_{p\in Ex} E_{c0} \Delta C1^f_{ct} C2^f_{cpt} T^f_{cpt} \\
&\quad + \sum_f \sum_{p\in Ex} E_{c0} C1^f_{c0} \Delta C2^f_{cp1} T^f_{cp1} + \sum_f \sum_{p\in Ex} E_{c0} C1^f_{c0} C2^f_{cp0} \Delta T^f_{cpt}
\end{aligned} \tag{16}$$

The right-hand of equation 16 provides the contribution of each effect (in order ΔI_E_{ct}, ΔI_C1_{ct}, ΔI_C2_{ct} and ΔI_T_{ct}). However, this solution isn't unique, because it depends on the order in which the effects are introduced into the analysis (see Dietzenbacher and Los, 1998). Dietzenbacher and Los specify that with n effects there are $n!$ decomposition forms. In our case we have four (4) effects, so 24 decomposition forms are possible, and 24 contributions for each effect depending on these decomposition forms. For example, we can decide to start the previous decomposition procedure from the last effect to the first, exactly the opposite of what is done in equation 16. In this way, the corresponding decomposition form will be :

$$\Delta I_{ct}^{Ex} = \sum_f \sum_{p \in Ex} \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cp0}^f + \sum_f \sum_{p \in Ex} E_{c1} \Delta C1_{ct}^f C2_{cp0}^f T_{cp0}^f$$
$$+ \sum_f \sum_{p \in Ex} E_{c1} C1_{c1}^f \Delta C2_{cp1}^f T_{cp0}^f + \sum_f \sum_{p \in Ex} E_{c1} C1_{c1}^f C2_{cp1}^f \Delta T_{cpt}^f \quad (17)$$

From equations 16 and 17, we can see different contributions for the same effect. Dietzenbacher and Los showed that the results are sensitive to the form of decomposition adopted in the analysis. They named equations 16 and 17 as the two polar decomposition forms. To solve this non-uniqueness problem, they propose to take for each effect the average of the contributions provided by the so-called polar decompositions. The reason is that this average is quite close to that obtained when using the contributions provided by the 24 decomposition forms. The contribution of each effect in these polar forms are mirror images of each other, i.e. opposite weights with respect to time, and they are not unique (Haan, 2001). As presented by Haan (2001), in 24 decomposition forms we will have 12 pairs of mirror images. Haan (2001) sensitivity analysis shows that any of the 12 mirror image pairs provide results that are quite close to that of the 24 decomposition forms. However, the averages from the 24 decomposition forms have a similar weighting structure, with respect to time, which is not the case for those obtained when using one of the 12 mirror image pairs. In other words, using the 24 decomposition forms to obtain the average contribution of each effect makes the approach symmetrical. This avoids arbitrary weight structure problem, raised by Jacobsen (2000), and allows mutual comparability between the different effects (see Jacobsen, 2000; Haan, 2001). The average contribution of the scale effect when using the 24 decomposition forms is identical to equation 13. Since in this case the approach is symmetric, then one can easily deduce the average contributions of other effects. These average contributions will be identical to the contributions obtained under the two previous decomposition approaches.

5 Statistical precision : significance test of effects

We can notice that the contribution of each effect obtained following Shapley' value and Sun's approaches is an average contribution when using the 24 decomposition forms of Dietzenbacher and Los's approach. For the scale effect of exports (or net exports), equations 13 and 15 show that the contribution of this effect is an average of 24 items (hereafter referred as intermediate contributions). To refer to Dietzenbacher and Los's approach, each of these intermediate contributions is derived from one of the 24 decomposition forms. These intermediate contributions (based on the weights of Laspeyres or Paasche) are presented in the formula 18.

$$\sum_f \sum_{p \in Ex} \left\{ \begin{array}{l} \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cp0}^f, \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cp0}^f, \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cp0}^f, \\ \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cp0}^f, \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cp0}^f, \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cp0}^f, \\ \Delta E_{ct} C1_{ct}^f C2_{cp0}^f T_{cp0}^f, \Delta E_{ct} C1_{ct}^f C2_{cp0}^f T_{cp0}^f, \Delta E_{ct} C1_{c0}^f C2_{cpt}^f T_{cp0}^f, \\ \Delta E_{ct} C1_{c0}^f C2_{cpt}^f T_{cp0}^f, \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cpt}^f, \Delta E_{ct} C1_{c0}^f C2_{cp0}^f T_{cpt}^f, \\ \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cp0}^f, \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cp0}^f, \Delta E_{ct} C1_{ct}^f C2_{cp0}^f T_{cpt}^f, \\ \Delta E_{ct} C1_{ct}^f C2_{cp0}^f T_{cpt}^f, \Delta E_{ct} C1_{c0}^f C2_{cpt}^f T_{cpt}^f, \Delta E_{ct} C1_{c0}^f C2_{cpt}^f T_{cpt}^f, \\ \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cpt}^f, \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cpt}^f, \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cpt}^f, \\ \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cpt}^f, \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cpt}^f, \Delta E_{ct} C1_{ct}^f C2_{cpt}^f T_{cpt}^f \end{array} \right\} \quad (18)$$

This formula provides the database for calculating the average contribution of the scale

effect of exports (or net exports) and estimating its statistical precision. By symmetry, we can easily find the databases for other effects. After identifying the intermediate contributions for each effect, it is necessary to show that there is variability between them. Otherwise, this would mean that any of the intermediate contributions would be a good estimate of the average contribution of the effect. Therefore, it would no longer be important to estimate the accuracy of the average contribution of the effect. As in Dietzenbacher and Los (1998), we will use the range (Maximum-Minimum) relative to the average and the coefficient of variation to analyze the dispersion of these intermediate contributions around the average contribution of each effect. In the case of high dispersion, then it would be important to know whether the average contribution of each effect is significantly different from zero or not. Indeed, additive decomposition studies currently identify the relevance of an effect only through its relative magnitude and the sign of its contribution. By doing so, studies can provide an economic misinterpretations and thereby propose "incorrect" policies, simply because the contribution of an effect may be statistically non-significant (i.e not significantly different from zero at standard significance levels). Thus, the accuracy of the average contribution of each effect allows researchers to be more cautious in analyzing the results and decision-makers to be aware of the margin of error of results they use to implement policies.

To achieve this, we need to construct confidence intervals (CI) for the average contribution of each effect as in equation 19. The distribution of the average contribution of each effect is unknown. When the distribution of a parameter (in our case the effect) is unknown, one possibility is to use the approximation to the normal distribution (see Poi, 2004). Indeed, at a significance level α, the equation 19 presents the CI for the average contribution of each effect :

$$CI = \left[\widehat{\theta} \mp Z_{1-\frac{\alpha}{2}} \times \sigma_{\hat{\theta}}\right] \tag{19}$$

Where $\widehat{\theta} = [\Delta I\_E_{ct} \ \Delta I\_C1_{ct} \ \Delta I\_C2_{ct} \ \Delta I\_T_{ct}]$ a line vector of the average contributions of the four effects depending on $I = \{Creations, Transfers\}$, and $\sigma_{\hat{\theta}} = [\sigma_{\Delta I\_E_{ct}} \ \sigma_{\Delta I\_C1_{ct}} \ \sigma_{\Delta I\_C2_{ct}} \ \sigma_{\Delta I\_T_{ct}}]$ a line vector of standard errors of average contributions. $Z_{1-\frac{\alpha}{2}}$ is the $(1-\alpha/2)$ quantile of the standard normal distribution. The method or hypothesis adopted for the estimation of $\sigma_{\hat{\theta}}$ depends on the number of observations (N) (see Poi, 2004). Indeed, $\sigma_{\hat{\theta}}$ can be estimated based on the asymptotic normal distribution, when N tends to infinity. However, the hypothesis of a student distribution can be used when N is small. In the case of finite N, as in our case $N = 24$, the estimate of $\sigma_{\hat{\theta}}$ from asymptotic distributions may have poor results. Instead, the estimate of $\sigma_{\hat{\theta}}$ can be obtained by the following sample standard deviation formula:

$$\widehat{\sigma}_{\widehat{\theta}} = \left[\frac{1}{K-1}\sum_{k=1}^{K}(\widehat{\theta}_k - \bar{\theta})\right]^{\frac{1}{2}} \tag{20}$$

Where $\left\{\widehat{\theta}\right\}_{k=1}^{K}$ are $\widehat{\theta}$ calculated with the bootstrap sample, K the number of replications and $\bar{\theta} = \frac{1}{K}\sum_{k=1}^{K}\widehat{\theta}$. Bootstrap is a technique that consists of randomly drawing a sample of 24 observations from the database $(N = 24)$ and calculating $\widehat{\theta}$ associated with this sample. This process is repeated K times and we obtain at the end of the process $\left\{\widehat{\theta}\right\}_{k=1}^{K}$ and their average $\bar{\theta}$. This allows us to adequately estimate $\sigma_{\hat{\theta}}$ by $\widehat{\sigma}_{\widehat{\theta}}$. Therefore, equation 19 becomes:

$$CI = \left[\widehat{\theta} \mp Z_{1-\frac{\alpha}{2}} \times \widehat{\sigma}_{\widehat{\theta}}\right] \tag{21}$$

This CI is known as "bootstrapped normal-approximation confidence interval"[16] (see Poi, 2004). With this method, according to Stata's manual on bootstrap method (see Stata, 2013), we do not need a very good estimate of the sample distribution, obtained through the bootstrap distribution, when we only want to estimate $\sigma_{\hat{\theta}}$. This is very important because the method is based on the assumption that the sample distribution estimated by the bootstrap distribution of $\left\{\widehat{\theta}\right\}_{k=1}^{K}$ is approximately normal. Thus, since IC are based on standard errors, the CI estimate can be considered acceptable if the assumption of a normal distribution is approximately true (see Stata, 2013). Thus, we will present the densities estimated with bootstrap samples in order to compare them to normal density.

In an additive decomposition, the interpretation of the contribution of each effect is made with respect to zero. Therefore, the intuition and interpretation of CI are the same as in an econometric analysis where we have the CI of each coefficient, or as for the CI of an average. If the p-value related to the CI of an effect is below the significance level (α), then the average contribution of this effect is statistically significant (i.e significantly different from zero) at this significance level.

The number of observations of the initial sample (here $N = 24$) and the number of replications (here K) are very important for the accuracy of bootstrap estimator (see Stata, 2013). The number of observations in the Shapley/Sun's approach increases with the number of effects. As mentioned above, with n effects, we will have $n!$ observations for the calculation of the average contribution of each effect. The estimation of the accuracy of each effect will be based on this $n!$ observations. This is an interesting point, as the average contribution of each effect should be more accurate when the number of effects is high. Therefore, the complexity of the Shapley/Sun's formula when the number of effects becomes large should not only be seen as a disadvantage, but also as a valuable advantage, as it should improve the results' accuracy. Consequently, unlike what is recommended or preferred in the literature, Shapley/Sun's approach should be preferred when the number of effects is large. Concerning the number of replications (K), the ideal would be to choose K as high as possible, but in practice it is necessary to arbitrate between accuracy and time cost to obtain results (see Poi, 2004). However, for the estimation of standard errors and the estimation of CI according to normal approximation, 50 to 200 replications are sufficient for an adequate estimation, although replications around 1000 produce better estimates (see Stata, 2013). In this paper, we have chosen a replication number ($K = 5000$) beyond this recommendation to ensure good estimates.

Overall, we believe that the ability of this approach (S/S) to provide the accuracy of each effect is a significant advantage that researchers should consider when choosing the decomposition approach for their studies. In this line, we therefore introduce a new criterion for the choice of an additive decomposition approach, which we refer to as "accuracy criterion". In other words, we extend the list of selection criteria proposed by Ang (2004), presented above, from 4 to 5 criteria.

6 Application results

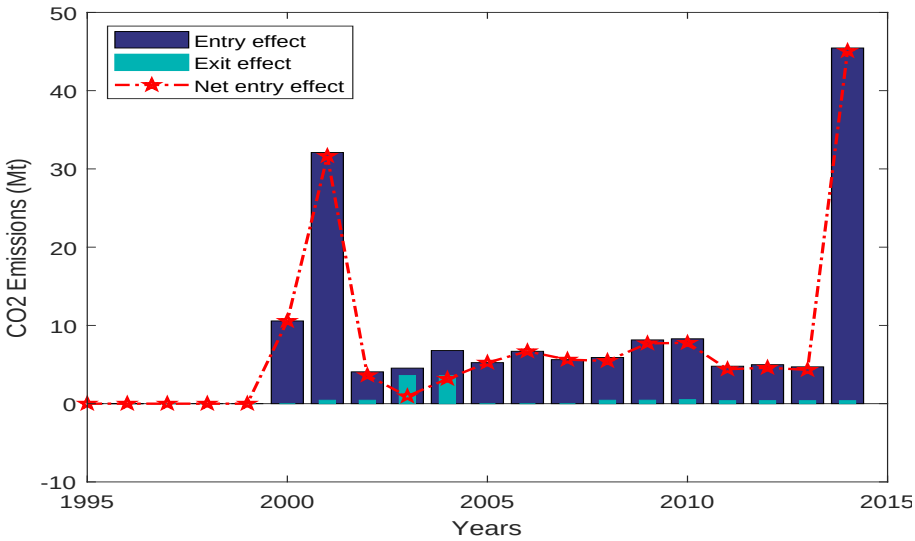
For the application, we use the database of Outchiri and He (2020). This database includes information on physical data of bilateral trade (in kg of export and import) between China and 181 trading

[16] See Poi (2004) for alternative methods.

partners (see Appendix A) at the level of 1033 products from 1995 to 2014, and the product-level emission intensities (in kg of CO2/kg of product) which vary across countries and over time[17].

6.1 Does net entry effect matter for effects' contribution estimation?

Figure 1 presents the entry effect, exit effect and net entry effect of traded products. Before 2000, the entry and exit effect are either zero or negligible, resulting in a negligible net entry effects. From 2000 onwards, the entry effect is positive and is greater than the exit effect. This led to a positive net entry effect that may have an impact on decomposition results if it is not accounted for in the analysis. We compare the results obtained without the net entry effect to those obtained with this effect to highlight how not considering this effect can affect the decomposition analysis results.



Note: Entry effect represents the part of EEBT due to new products traded. Exit effect refers to the part of EEBT due to products that are no longer traded. The difference between the first and the second represents the net entry effect.
Source: Author.

Figure 1: Entry effect, Exit effect and Net entry effect.

Appendix B (see Table 4) provides the changes in EEBT, the changes in the new emission creations and those in real emission transfers depending on whether or not the net entry effect is taken into account. This appendix also reports information on both the contribution of the net entry effect and the number of products in the set of existing, entering and exiting products each year. To facilitate the comparison of the results obtained with versus without the net entry effect, this appendix sets out the "change rate"[18] of the contribution of new emissions creations

[17] Outchiri and He (2020) used three data sources to build their database. The product-level bilateral trade data come from BACI database of CEPII (2016). Gaulier and Zignago (2010) provide more information on this bilateral trade database. To compute product-level emission intensities which vary across countries and over time, Outchiri and He (2020) used countries' CO2 emission intensities from 1995 to 2014 (sourced fromWDI (2017)) to adjust world average ecological footprint coefficients of products (sourced from Sato (2014)) under 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. More details on the construction of the database can be found in Outchiri and He (2020).

[18] The change rate of the contribution of new emission creations is computed as the difference between the $\Delta Creations$ (respectively $\Delta Transfers$) obtained with net entry effect and that obtained without net entry effect divided by the $\Delta Creations$ (respectively $\Delta Transfers$) obtained without net entry effect. For example, if the change rate of the contribution of new emission creations is 10% (respectively -10%), this would mean that taking into account

(respectively real emission transfers) between with and without net entry effect.

The results in Appendix B (see Table 4) reveal that omitting net entry effect can lead to under- or overestimation of the contribution of new emission creations ($\Delta Creations$) and that of real emission transfers ($\Delta Transfers$). Indeed, we can observe that the change rate of $\Delta Creations$ and/or $\Delta Transfers$ for some years such as 2000, 2001, 2002, 2003 and 2014 are very high. For example, in 2001, compared to 1995, EEBT decreased by 32.03 Mt of CO2. If we do not consider the net entry effect, this reduction in EEBT can be explained by a reduction in new emission creations of 52.53 Mt of CO2 combined with an increase in real emission transfers of 20.50 Mt of CO2. However, when we consider the net entry effect, we note that the reduction in EEBT in 2000 is due to a reduction in new emission creations of 74.03 Mt of CO2 together mainly with a positive contribution of the net entry effect of 31.65 Mt of CO2 followed by an increase in real emission transfers of 10.34 Mt of CO2. As a result, when the net entry effect is included, the contribution of new emission creations increased by 40.92%, while that of real emission transfers decreased by 49.54%. In other words, failure to consider the net entry effect will lead to a large underestimation of the contribution of new emission creations and a considerable overestimation of that of real emission transfers. The same reasoning allows us to conclude to an underestimation of the contribution of new emission creations in 2000 and 2002, and an overestimation (respectively underestimation) of the contribution of real emission transfers in 2000 and 2014 (respectively in 2002 and 2003). For other years, we can also observe changes but they are relatively very small. Thus, this first analysis suggests that whether or not we consider the net entry effect could have an impact on the decomposition results.

Tables 1 and 2 show the decomposition results (without and with taking into account the net entry effect) for new emission creations and real emission transfers. As previously, to facilitate comparison of the decomposition results between with and without the net entry effect, Table 3 reports the "change rate" of the contribution of each effect [19]. First, not surprisingly, we notice that with low entry and exit of products leading to a negligible net entry effect, such as from 1996 to 1999 (see Figure 1 and Table 4 in Appendix B), whether or not the net entry effect is taken into account does not appear to affect the decomposition results (see for example Tables 1 and 2 from 1996 to 1999). This is directly observed in Table 3, where the change rates of the contributions of each effect are roughly zero from 1996 to 1999.

Second, for other years where the movements (entry and exit) of products are relatively larger, we can find evidence that although the net entry effect is smaller than that of most other effects presented in Tables 1 and 2, it even influences the decomposition results. Indeed, as the above analysis revealed for the years from 2000 to 2003 and 2014 that there was an under- or over-estimation of the contribution of new emission creations and/or real emission transfers, we therefore begin by comparing the decomposition results for these years. For example, for the year 2001 we notice an important change in the contributions of within-partner composition effect of exports, between-partner composition effect of net exports and within-partner composition effect of net exports (see Table 3). After accounting for the net entry effect (see Tables 1 and 2), the

the net entry effect increases (respectively decreases) the contribution of new emission creations by 10%.

[19] Table 3 is compiled by applying the definition of the change rate to the decomposition results reported in Tables 1 and 2.

Table 1: Decomposition results for new emission creations and significance

	Without net entry effect				With net entry effect			
	Scale	B-P composition	W-P composition	Technical gap	Scale	B-P composition	W-P composition	Technical gap
main								
1996	10.54***	-3.823***	-8.466***	-26.52***	10.54***	-3.823***	-8.466***	-26.52***
	(0.0876)	(1.101)	(1.063)	(0.0800)	(0.0884)	(1.112)	(1.062)	(0.0812)
1997	88.41***	-9.693***	-3.548***	-74.57***	88.41***	-9.694***	-3.548***	-74.57***
	(1.740)	(1.110)	(1.080)	(1.596)	(1.709)	(1.126)	(1.072)	(1.568)
1998	49.01***	23.95***	-7.661***	-121.4***	49.01***	23.95***	-7.661***	-121.4***
	(1.531)	(1.243)	(0.851)	(1.895)	(1.497)	(1.230)	(0.839)	(1.908)
1999	210.1***	-84.02***	36.65***	-181.5***	210.1***	-84.03***	36.65***	-181.5***
	(10.75)	(4.388)	(2.457)	(9.262)	(10.72)	(4.493)	(2.438)	(9.200)
2000	171.8***	-14.95***	-9.157***	-198.2***	169.4***	-15.91***	-14.56***	-196.3***
	(8.918)	(1.928)	(1.804)	(8.116)	(9.055)	(2.043)	(2.070)	(7.979)
2001	190.3***	-15.62***	2.785	-230.0***	184.0***	-15.99***	-20.08***	-222.0***
	(11.11)	(2.763)	(2.628)	(10.68)	(10.86)	(2.733)	(2.840)	(9.830)
2002	232.0***	-20.37***	-11.86***	-226.2***	230.4***	-20.75***	-13.83***	-225.1***
	(13.13)	(3.215)	(2.936)	(11.74)	(13.02)	(3.166)	(2.994)	(11.95)
2003	352.1***	-14.13**	-9.218*	-217.5***	352.0***	-14.46**	-10.19**	-215.9***
	(16.14)	(5.592)	(5.113)	(15.45)	(15.98)	(5.731)	(5.109)	(15.20)
2004	430.9***	20.00***	49.01***	-209.2***	430.0***	19.57***	47.07***	-207.4***
	(14.72)	(2.350)	(3.728)	(16.72)	(14.33)	(2.386)	(3.633)	(16.45)
2005	526.0***	21.82***	67.88***	-209.0***	523.4***	21.33***	65.52***	-208.3***
	(16.34)	(5.193)	(6.781)	(18.18)	(16.27)	(5.206)	(6.760)	(18.38)
2006	705.5***	44.60***	93.86***	-250.5***	702.4***	44.03***	90.82***	-249.6***
	(22.94)	(8.708)	(10.98)	(26.29)	(22.33)	(8.329)	(10.91)	(26.31)
2007	856.2***	51.44***	145.1***	-338.4***	853.2***	50.87***	142.5***	-337.4***
	(34.56)	(13.34)	(18.63)	(38.70)	(33.68)	(13.26)	(18.20)	(38.32)
2008	823.0***	46.67***	183.2***	-357.7***	820.5***	46.08***	180.4***	-356.5***
	(36.26)	(14.39)	(22.12)	(40.58)	(36.57)	(14.59)	(22.10)	(40.26)
2009	481.9***	40.12***	184.2***	-320.6***	479.3***	39.53***	180.1***	-318.8***
	(24.19)	(14.15)	(18.78)	(29.30)	(24.16)	(14.00)	(18.47)	(29.12)
2010	730.5***	48.05***	241.4***	-396.4***	727.3***	47.33***	237.6***	-394.6***
	(39.06)	(17.87)	(27.04)	(44.58)	(37.70)	(17.64)	(27.10)	(44.16)
2011	858.8***	37.52*	299.8***	-419.9***	856.4***	36.92*	297.1***	-418.7***
	(45.79)	(22.49)	(35.77)	(49.92)	(45.45)	(22.32)	(36.20)	(50.62)
2012	885.4***	6.482	302.6***	-483.4***	882.9***	6.087	299.9***	-482.0***
	(51.99)	(27.67)	(40.08)	(60.27)	(53.46)	(28.07)	(40.56)	(59.96)
2013	872.5***	5.238	296.2***	-525.2***	870.2***	4.676	293.5***	-523.8***
	(56.04)	(28.44)	(41.92)	(65.62)	(55.43)	(29.13)	(41.78)	(65.00)
2014	988.6***	9.615	306.8***	-652.0***	982.4***	7.301	298.2***	-644.0***
	(72.82)	(31.03)	(47.00)	(85.88)	(71.56)	(31.02)	(44.64)	(85.04)
N	456	456	456	456	456	456	456	456

Note: Bootstrapped standard errors in parentheses based on 5000 replications ($***p < 0.01, **p < 0.05, *p < 0.1$). Scale effect of exports (Scale), between-partner composition effect of exports (B-P composition), within-partner composition effect of exports (W-P composition) and technical gap effect (Technical gap) are the effects related to new emission creations.
Source: Author.

contribution of within-partner composition effect of exports fell from 2.78 to -20.08 Mt of CO2 (which represents a decrease of 820%), the contribution of within-partner composition effect of net exports decreased from 4.86 to -22.01 Mt of CO2 (i.e. a decrease of -552.58%), while that of between-partner composition effect of net exports increased by 45% (rising from 53.01 to 77.36 Mt of CO2). It is useful to mention that the sign of the first two contributions have changed, which reverses the interpretation of the contributions of these effects[20]. Also, one can remark (from Table 3) that when the net entry effect is taken into account, the decomposition results for the

[20]We recall that when the contribution of the effect is positive (negative), this means that the effect contributes to increase (reduce) the decomposed aggregate (here new emission creations, or real emission transfers or EEBT).

Table 2: Decomposition results for real emission transfers and significance

	Without net entry effect				With net entry effect			
	Scale	B-P composition	W-P composition	Technique	Scale	B-P composition	W-P composition	Technique
main								
1996	-3.524***	-31.54***	11.67***	-2.191***	-3.524***	-31.54***	11.67***	-2.191***
	(0.0880)	(0.726)	(0.761)	(0.172)	(0.0875)	(0.733)	(0.770)	(0.177)
1997	-17.47***	119.7***	-109.4***	8.227***	-17.47***	119.7***	-109.4***	8.227***
	(2.063)	(27.64)	(26.50)	(0.498)	(2.042)	(28.02)	(26.30)	(0.491)
1998	-8.902***	19.66***	-9.454	9.591***	-8.902***	19.66***	-9.454	9.591***
	(0.343)	(6.509)	(6.855)	(0.517)	(0.344)	(6.496)	(6.743)	(0.520)
1999	22.26***	17.87***	38.79***	11.11***	22.26***	17.87***	38.80***	11.11***
	(2.073)	(4.110)	(5.083)	(1.114)	(2.127)	(4.144)	(4.984)	(1.097)
2000	-32.53***	-14.16***	37.44***	20.77***	-33.96***	-7.749***	28.07***	21.41***
	(1.331)	(1.293)	(1.742)	(1.026)	(1.193)	(2.438)	(2.713)	(1.015)
2001	-64.78***	53.01***	4.864	27.41***	-70.80***	77.36***	-22.01*	25.80***
	(4.196)	(8.080)	(8.193)	(3.784)	(5.162)	(12.63)	(11.39)	(2.975)
2002	-155.1***	244.4***	-130.9**	39.48***	-174.9***	330.9***	-202.2***	43.26***
	(25.38)	(62.20)	(53.55)	(6.117)	(34.03)	(81.13)	(70.99)	(7.888)
2003	-158.6***	6.700	110.6***	38.68***	-160.1***	12.83*	104.9***	38.56***
	(13.49)	(6.794)	(13.91)	(4.305)	(13.02)	(7.738)	(13.78)	(4.262)
2004	-136.3***	-105.4***	249.4***	32.97***	-146.6***	-91.54***	242.9***	34.19***
	(36.85)	(32.41)	(36.94)	(7.540)	(34.49)	(25.89)	(33.58)	(7.281)
2005	-1009.6***	2330.0***	-1206.5***	-19.29	-408.0***	588.9***	-129.2	42.27***
	(363.9)	(585.2)	(437.8)	(37.21)	(87.67)	(147.4)	(110.3)	(9.784)
2006	-273.3***	276.8***	135.8**	35.48***	-175.9***	19.55**	308.8***	21.53
	(50.11)	(64.49)	(53.97)	(12.28)	(48.14)	(9.264)	(43.35)	(14.78)
2007	-111.6	9.974	385.1***	-14.28	-111.6	8.639	385.8***	-14.19
	(67.93)	(31.62)	(63.07)	(27.19)	(68.28)	(31.94)	(62.78)	(26.72)
2008	-253.2***	329.4***	210.8***	17.47	-256.6***	345.5***	198.0***	16.95
	(69.43)	(61.67)	(48.77)	(20.78)	(68.98)	(65.69)	(48.02)	(20.75)
2009	-443.7***	-105.8*	531.5***	73.45**	-481.0***	-16.22	485.5***	64.90**
	(118.7)	(60.22)	(105.9)	(29.87)	(108.6)	(38.72)	(91.61)	(30.41)
2010	-268.9	-385.4**	852.1***	-40.33	-299.3	-328.7**	807.6***	-23.99
	(207.0)	(149.9)	(205.3)	(80.31)	(191.4)	(131.5)	(191.7)	(71.62)
2011	-528.7***	-230.0***	825.4***	61.92	-554.4***	-176.2***	794.0***	65.38
	(179.5)	(76.84)	(161.2)	(47.17)	(171.5)	(62.18)	(155.3)	(45.85)
2012	-723.8***	-6.097	788.6***	104.5**	-723.7***	-10.57	792.9***	104.2**
	(166.4)	(12.09)	(148.4)	(52.46)	(170.6)	(11.82)	(150.5)	(52.57)
2013	-310.6	-1097.6***	1497.7***	27.88	-5087.8***	8327.3***	-4154.7**	1032.4*
	(387.7)	(312.3)	(386.0)	(100.5)	(1942.9)	(2443.3)	(2056.3)	(569.6)
2014	-599.0**	-254.8***	1056.7***	132.2*	-677.0***	-135.0***	967.0***	144.2*
	(234.9)	(73.45)	(217.3)	(76.89)	(216.9)	(39.15)	(192.7)	(74.32)
N	456	456	456	456	456	456	456	456

Note: Bootstrapped standard errors in parentheses based on 5000 replications ($***p < 0.01, **p < 0.05, *p < 0.1$). Scale effect of net exports (Scale), between-partner composition effect of net exports (B-P composition), within-partner composition effect of net exports (W-P composition) and partners' technical effect (Technique) are the effects related to real emission transfers.
Source: Author.

years 2000, 2002, 2003 and 2014 undergo some noticeable changes, especially for the contributions of between-partner composition effect of exports (in 2014), within-partner composition effect of exports (in 2000, 2002 and 2003), scale effect of net exports (in 2002 and 2014), between-partner composition effect of net exports (in 2000, 2002 and 2003) and within-partner composition effect of net exports (in 2000 and 2002).

Turning to other years (i.e. from 2004 to 2013), even if accounting for net entry effect does not seem to have considerable influence on the contributions of new emission creations and real emission transfers (see Table 4 in Appendix B), this may strongly affect the decomposition results

Table 3: Change rates between with and without NEE for each effect (in %)

Years	New emission creations				Real emission transfers			
	Scale	B-P composition	W-P composition	Technical gap	Scale	B-P composition	W-P composition	Technique
1996	-0.19 10^3	-0.28 10^3	2.59 10^3	-0.03 10^3	0.23 10^3	-0.03 10^3	-0.26 10^3	-0.01 10^3
1997	0.61 10^3	3.81 10^3	-3.22 10^3	-0.12 10^3	-1.46 10^3	-0.17 10^3	-1.03 10^3	0.05 10^3
1998	1.07 10^3	-1.65 10^3	-1.43 10^3	-0.12 10^3	-1.74 10^3	0.23 10^3	10.19 10^3	0.19 10^3
1999	0.26 10^3	0.53 10^3	3.23 10^3	-0.09 10^3	1.57 10^3	-3.32 10^3	3.54 10^3	0.41 10^3
2000	-1.42	6.39	58.97	-0.99	4.37	-45.26	-25.03	3.08
2001	-3.31	2.40	-820.90	-3.49	9.29	45.93	-552.58	-5.86
2002	-0.68	1.87	16.63	-0.50	12.75	35.39	54.47	9.57
2003	-0.05	2.33	10.55	-0.75	0.92	91.43	-5.12	-0.32
2004	-0.20	-2.12	-3.96	-0.88	7.57	-13.16	-2.63	3.70
2005	-0.48	-2.27	-3.48	-0.35	-59.59	-74.73	-89.29	-319.07
2006	-0.44	-1.28	-3.23	-0.38	-35.63	-92.94	127.33	-39.33
2007	-0.34	-1.11	-1.79	-0.29	-0.02	-13.38	0.18	-0.69
2008	-0.31	-1.26	-1.52	-0.33	1.35	4.86	-6.07	-2.98
2009	-0.53	-1.46	-2.23	-0.56	8.41	-84.67	-8.64	-11.64
2010	-0.44	-1.52	-1.56	-0.45	11.30	-14.71	-5.22	-40.51
2011	-0.28	-1.61	-0.90	-0.29	4.87	-23.39	-3.80	5.60
2012	-0.29	-6.08	-0.91	-0.28	-0.02	73.37	0.55	-0.26
2013	-0.27	-10.73	-0.90	-0.27	1537.85	-858.67	-377.40	-3603.24
2014	-0.63	-24.06	-2.80	-1.22	13.02	-47.02	-8.49	9.10

Note: *NEE* means net entry effect. The change rates of scale effect of exports (Scale), between-partner composition effect of exports (B-P composition), within-partner composition effect of exports (W-P composition) and technical gap effect (Technical gap) are the percentage change between without and with NEE of each effect related to new emission creations. The change rates of scale effect of net exports (Scale), between-partner composition effect of net exports (B-P composition), within-partner composition effect of net exports (W-P composition) and partners' technical effect (Technique) are the percentage change between without and with NEE of each effect related to real emission transfers. For example, the change rates of *Scale* is computed as the difference between the *Scale* obtained with NEE and that obtained without NEE divided by the *Scale* obtained without NEE. The same procedure is used to compute the change rates for other effects. The results are in percentage.
Source: Author.

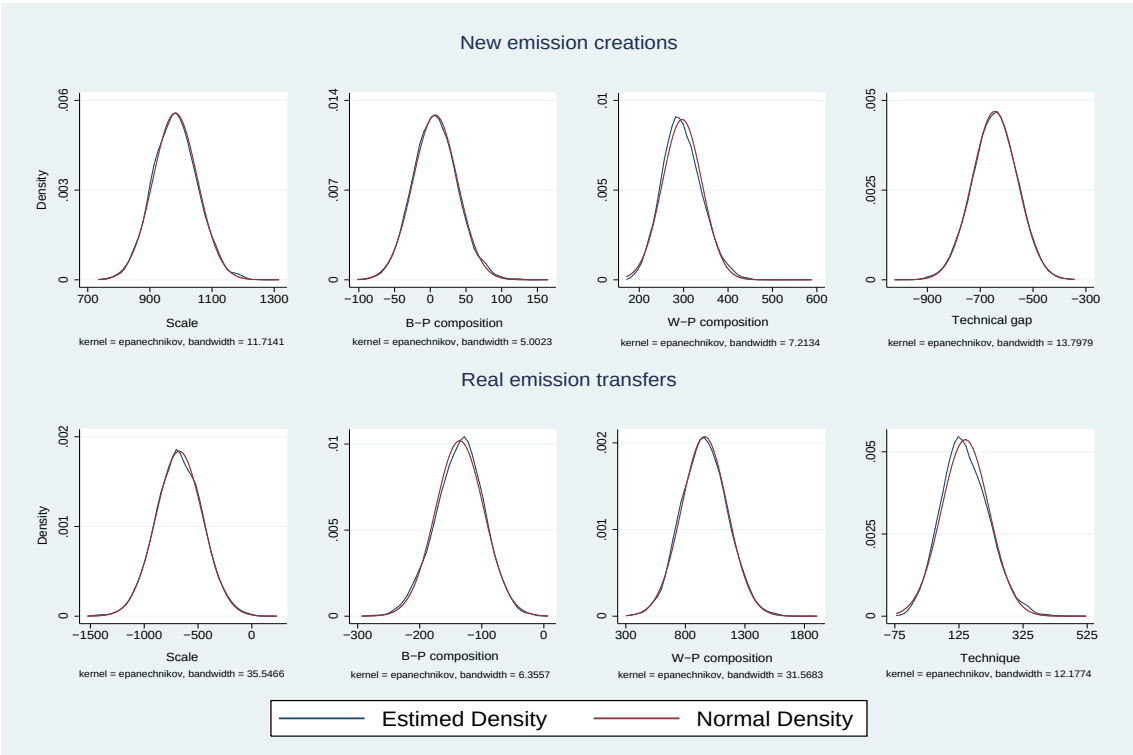
(see Tables 1, 2 and 3). For example, for the years 2005, 2006 and 2013 we can see in Table 3 that the change rates for all four effects explaining real emission transfers are quite high. Moreover, in 2005 we also note a modification of the sign of the contribution of partners' technical effect (from -19.29 to 42.27 Mt of CO2) when net entry effect is considered (see Table 2). This completely changes the interpretation of this result. Also, the influence of accounting for net entry effect on the contributions of other effects is not proportional, which can lead to a change in the order of magnitude of the contributions within a given year. In fact, if the order of magnitude of the contributions changes, then the relative importance of each effect in explaining the phenomenon (here new emission creations, real emission transfers or EEBT) will be altered. For illustration, in 2006, by ranking the contributions of the eight effects in decreasing order, the contribution of between-partner composition effect of net exports moves from second to sixth place when considering the net entry effect. Therefore, this effect becomes less relevant (or in other words, other effects become more relevant) when the net entry effect is taken into account.

Thus, it emerges from our analysis that not accounting for the net entry effect can lead to under- or over-estimates, wrong signs and even a wrong order of magnitude of the contributions of the effects. Consequently, the analysis will be based on biased results and will therefore lead to "incorrect" policy proposals.

6.2 Why is it useful to estimate the effects' accuracy?

Appendix B (see Table 5) presents for each effect the range relative to the average (RR) and the coefficient of variation (CV) in percentage. These statistics allow us to analyze the dispersion around the average contribution. For example, for the year 2014, the range and the standard deviation represent respectively 116.56% and 35.69% of the average contribution of the scale effect of exports. It can be seen in Appendix B (see Table 5) that the variability around the average contributions of each effect is very high. Dietzenbacher and Los (1998) also found strong variability around the average contribution of each effect, and they propose that the results of decomposition analysis should be reported together with these two dispersion statistics (RR and CV). These two statistics obviously allow us to appreciate the dispersion around the average contribution of each effect, but they do not inform us whether the results are accurate or not. So we use this dispersion to estimate the accuracy of each effect through "bootstrapped normal-approximation confidence interval".

Figure 2 reports the densities estimated by the bootstrap samples for 2014 and the normal density. In 2014, the comparison of estimated density for each effect to normal density reveals that the assumption that the sample distribution estimated by bootstrap distribution is approximately normal seems to be approximately true. This conclusion is valid for other years[21].



Note: Scale effect of exports (Scale), between-partner composition effect of exports (B-P composition), within-partner composition effect of exports (W-P composition) and technical gap effect (Technical gap) are the effects related to new emission creations. Scale effect of net exports (Scale), between-partner composition effect of net exports (B-P composition), within-partner composition effect of net exports (W-P composition) and partners' technical effect (Technique) are the effects related to real emission transfers. 5000 bootstrap replications.
Source: Author.

Figure 2: Densities estimated with 2014 bootstrap sample and Normal density.

[21] Results for other years are not presented in order to save space, but are available upon request.

Tables 1 and 2 display the standard errors and significance of each effect obtained through "bootstrapped normal-approximation confidence interval". In these tables, the standard errors of the average contributions are in parentheses, and the stars indicate the different levels (1%, 5%, and 10%) of statistical significance of the average contributions. We analyze the results that consider the net entry effect. First, we can remark that the contributions of the effects are statistically different from zero at different significance levels. For illustration, in 2003 the contribution of the scale effect of exports is statistically significant at 1%, while that of within-partner effect of exports and that of between-partner effect of net exports are statistically significant at 5% and 10% respectively. In other words, the contribution of the scale effect of exports (352 Mt of CO2 with a standard error of 15.98) is significantly different from zero at 1% level. However, the accuracy of the within-partner effect of exports (-10.19 Mt of CO2 with a standard error of 5.11) and that of between-partner effect of net exports (12.83 Mt of CO2 with a standard error of 7.74) are relatively weak, as their contributions are significantly different from zero only at 5% and 10% levels respectively.

Second, the results point out that some contributions are not statistically significant (see the contributions without stars in Tables 1 and 2). For example, looking at the effects that explain the real emission transfers in 2007 (see Table 2) we conclude that only one out of the four contributions is statistically different from zero. Among the contributions that are non-significantly different from zero at standard significance levels, we have that of scale effect of net exports. The contribution of this effect is not negligible in terms of magnitude (-111.6 Mt of CO2 with a standard error of 68.28), because it represents the main effect that increases the real emission transfers from China to its partners, and the second most important effect that helps to reduce China's EEBT (after the technical gap effect which accounts for -394.6 Mt of CO2). However, this effect is not statistically significant at standard significance levels, which means that we are not confident (at least at standard significance levels) about the estimated contribution of this effect. In this case, we will avoid interpreting the contribution of this effect (and also for all effects not statistically significant at standard significance levels), or at least be more cautious in our interpretations. This will lead to more robust policy proposals.

Therefore, since our analysis suggests that the effects may have different accuracy levels and that some effects (even those with large magnitude contributions) may be non-statistically significant at standard significance levels, then estimating the effects' accuracy is useful in order to be more accurate and confident in both interpreting the results and policy-making.

6.3 Does net entry effect matter for effects' accuracy estimation?

In this session we compare, in Tables 1 and 2, the statistical accuracy of each effect between without and with the net entry effect. The aim of this comparison is to explore whether accounting for the net entry effect may influence the effects' accuracy. We can observe that the effects' accuracy may depend on whether or not the net entry effect is included in the analysis. This can be illustrated by several examples from Tables 1 and 2, but the most salient are those from the years 2001, 2003, 2005, 2006, 2009 and 2013. Indeed, when we consider the net entry effect in 2001, the within-partner composition effect of exports and the within-partner composition effect of net exports (which are not statistically significant when we do not consider the net entry effect)

become statistically significant at 10% and 1% levels respectively. Similar changes are observed in 2003 (where the between-partner composition effect of net exports becomes statistically significant at 10% level), in 2005 (where the partners' technical effect becomes statistically significant at 1% level) and in 2013 (where both the scale effect of net exports and the partners' technical effect become statistically significant at 1% and 10% levels respectively). Also, inverse changes are observed, i.e. effects that turn out to be non-statistically significant when we consider the net entry effect. In 2006 (respectively 2009), the partners' technical effect (respectively the between-partner composition effect of net exports) changed from statistically significant at 1% level (respectively 10% level) to non-statistically significant when we consider the net entry effect. Other examples in Tables 1 and 2 illustrate changes (decrease or increase) in significance levels when we compare results without and with the net entry effect.

Thus, as argued above, accounting for the net entry effect can influence the estimation of the effects' accuracy. Consequently, considering the net entry effect also appears to be useful in order to adequately estimate the effects' accuracy. This may also contribute to more accurate analysis of decomposition results and thereby can lead to better policy-making.

7 Conclusion

This paper argues that decomposition analyses tend to be approach-dependent and so far do not indicate whether the results are accurate or not, which could make these analyses unreliable. This is problematic in terms of economic interpretations and policy-making, as most decomposition studies are policy-oriented, particularly in energy and environment-related fields. Therefore, we propose to estimate the standard errors (or confidence intervals) of each relative contribution using bootstrapped normal-approximation confidence interval in order to investigate whether or not each effect is significantly different from zero at standard significance levels. We also analyze how product movements (entry and exit effect, or net entry effect), in highly disaggregated data at product level, could affect the decomposition analysis results if they are not taken into account. To achieve this, we exploit the complexity of the S/S's decomposition approach. Therefore, our work introduces a new criterion for the choice of decomposition approaches, so-called accuracy criterion. The application is based on a decomposition of CO2 emissions embodied in China's bilateral trade (EEBT).

The results show that omitting the net entry effect can lead to under- or over-estimates of the contributions, wrong signs and even a wrong order of magnitude of the contributions, and incorrect estimation of the effects' accuracy. Also, the analyses reveal that the effects may have different accuracy levels and some effects (even those with large magnitude contributions) may be non-significantly different from zero at standard significance levels (1%, 5%, 10%). This means that there are effects (obviously those that are not significantly different from zero) that are not relevant to the explanation of China's EEBT. Our results therefore suggest that not considering the net entry effect or not being aware of the effects' accuracy may lead to incorrect economic interpretations and misguided policy-making. Another interesting point arising from the methodology is that the complexity of the S/S's approach, as the number of effects increases, should go hand in hand with the results' accuracy. Hence, when the number of effects becomes large the S/S's approach should not only be seen as a disadvantage, but also as a valuable advantage, as it should improve the accuracy of each effect. From this standpoint, the S/S's approach should be

preferred when the number of effects is high, contrary to what is stated in the literature.

Thus, as a desirable additional property of decomposition approaches, S/S's decomposition approach enables researchers and practitioners to test the accuracy of decomposition analysis results. Indeed, knowing whether results are accurate or not helps to strengthen their reliability and contributes to robust policy-making. As a result, more accurate results will help researchers and policy makers to feel more confident with their economic interpretations and policy-making. Although the application was made within the IDA framework, our proposal can be applied in the same way through the SDA framework.

References

Albrecht, J., François, D., and Schoors, K. (2002). A Shapley decomposition of carbon emissions without residuals. *Energy Policy*, 30(9):727–736.

Ang, B., Huang, H., and Mu, A. (2009). Properties and linkages of some index decomposition analysis methods. *Energy Policy*, 37(11):4624 – 4632.

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

Ang, B. W. (2015). LMDI decomposition approach: A guide for implementation. *Energy Policy*, 86:233–238.

Ang, B. W. and Choi, K.-H. (1997). Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method. *The Energy Journal*, 18(3):59–73.

Ang, B. W., Liu, F. L., and Chew, E. P. (2003). Perfect decomposition techniques in energy and environmental analysis. *Energy Policy*, 31(14):1561–1566.

Ang, B. W., Liu, F. L., and Chung, H.-S. (2004). A generalized Fisher index approach to energy decomposition analysis. *Energy Economics*, 26(5):757–763.

Ang, B. W. and Liu, N. (2007a). Handling zero values in the logarithmic mean Divisia index decomposition approach. *Energy Policy*, 35(1):238–246.

Ang, B. W. and Liu, N. (2007b). Negative-value problems of the logarithmic mean Divisia index decomposition approach. *Energy Policy*, 35(1):739–742.

Ang, B. W., Mu, A., and Zhou, P. (2010). Accounting frameworks for tracking energy efficiency trends. *Energy Economics*, 32(5):1209–1219.

Ang, B. W. and Zhang, F. Q. (2000). A survey of index decomposition analysis in energy and environmental studies. *Energy*, 25(12):1149–1176.

Ang, B. W., Zhang, F. Q., and Choi, K.-H. (1998). Factorizing changes in energy and environmental indicators through decomposition. *Energy*, 23(6):489–495.

Antweiler, W., Copeland, B. R., and Taylor, M. S. (2001). Is Free Trade Good for the Environment? *American Economic Review*, 91(4):877–908.

Barrows, G. and Ollivier, H. (2016). Emission intensity and firm dynamics: reallocation, product mix, and technology in India. GRI Working Papers 245, Grantham Research Institute on Climate Change and the Environment.

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

Cherniwchan, J., Copeland, B. R., and Taylor, M. S. (2017). Trade and the Environment: New Methods, Measurements, and Results. *Annual Review of Economics*, 9(1):59–85.

Copeland, B. R. and Taylor, M. S. (2004). Trade, Growth, and the Environment. *Journal of Economic Literature*, 42(1):7–71.

Dietzenbacher, E. and Los, B. (1998). Structural Decomposition Techniques: Sense and Sensitivity. *Economic Systems Research*, 10(4):307–323.

Ding, T., Ning, Y., and Zhang, Y. (2018). The contribution of Chinas bilateral trade to global carbon emissions in the context of globalization. *Structural Change and Economic Dynamics*, 46:78–88.

Dong, Y., Ishikawa, M., Liu, X., and Wang, C. (2010). An analysis of the driving forces of CO2 emissions embodied in JapanChina trade. *Energy Policy*, 38(11):6784–6792.

Fengling, L. (2005). *Decomposition analysis applied to energy: Some methodological issues*. Thesis.

Gaulier, G. and Zignago, S. (2010). Baci: International trade database at the product-level. the 1994-2007 version. Working Papers 2010-23, CEPII.

Grossman, G. M. and Krueger, A. B. (1991). Environmental Impacts of a North American Free Trade Agreement. Working Paper 3914, National Bureau of Economic Research.

Haan, M. D. (2001). A structural decomposition analysis of pollution in the netherlands. *Economic Systems Research*, 13(2):181–196.

He, J. and Jacquemin, J. (2016). La balance du carbone incorporé au commerce bilatéral entre la France et la Chine : transferts démissions ou nouvelles créations ?, Balance of carbon embodied in bilateral trade between France and China: transfer of emission or new creation? *Revue économique*, 67(6):1179–1210.

Hoekstra, R. and van den Bergh, J. C. J. M. (2003). Comparing structural decomposition analysis and index. *Energy Economics*, 25(1):39–64.

Jacobsen, H. K. (2000). Energy Demand, Structural Change and Trade: A Decomposition Analysis of the Danish Manufacturing Industry. *Economic Systems Research*, 12(3):319–343.

Lenzen, M. (2011). Aggregation versus Disaggregation in Input-Output Analysis of the Environment. *Economic Systems Research*, 23(1):73–89.

Lenzen, M., Pade, L.-L., and Munksgaard, J. (2004). CO2 Multipliers in Multi-region Input-Output Models. *Economic Systems Research*, 16(4):391–412.

Levinson, A. (2009). Technology, International Trade, and Pollution from US Manufacturing. *American Economic Review*, 99(5):2177–2192.

Outchiri, B. N. and He, J. (2020). Technical gap, trade partners and product mix evolution: how trading with China affects global CO2 emissions. Cahiers de recherche 20-07, Departement d'Economique de l'École de gestion à l'Université de Sherbrooke.

Poi, B. P. (2004). From the Help Desk: Some Bootstrapping Techniques. *The Stata Journal: Promoting communications on statistics and Stata*, 4(3):312–328.

Sato, M. (2014). Product level embodied carbon flows in bilateral trade. *Ecological Economics*, 105:106–117.

Shapley, L. S. (1953). A value for n-person games. *Contributions to the Theory of Games*, (28):307–317.

Stata (2013). bootstrap Bootstrap sampling and estimation. Manuals.

Su, B. and Ang, B. W. (2012). Structural decomposition analysis applied to energy and emissions: Some methodological developments. *Energy Economics*, 34(1):177–188.

Su, B., Huang, H. C., Ang, B. W., and Zhou, P. (2010). Inputoutput analysis of CO2 emissions embodied in trade: The effects of sector aggregation. *Energy Economics*, 32(1):166–175.

Sun, J. W. (1998). Changes in energy consumption and energy intensity: A complete decomposition model. *Energy Economics*, 20(1):85–100.

Wang, H., Ang, B. W., and Su, B. (2017a). Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. *Energy Policy*, 107:585–599.

Wang, H., Ang, B. W., and Su, B. (2017b). Multiplicative structural decomposition analysis of energy and emission intensities: Some methodological issues. *Energy*, 123:47–63.

WDI (2017). World Development Indicators database.

Wood, R. and Lenzen, M. (2006). Zero-value problems of the logarithmic mean divisia index decomposition method. *Energy Policy*, 34(12):1326–1331.

Wu, R., Geng, Y., Dong, H., Fujita, T., and Tian, X. (2016). Changes of CO2 emissions embodied in ChinaJapan trade: drivers and implications. *Journal of Cleaner Production*, 112:4151–4158.

Wyckoff, A. W. and Roop, J. M. (1994). The embodiment of carbon in imports of manufactured products: Implications for international agreements on greenhouse gas emissions. *Energy Policy*, 22(3):187–194.

Xu, X. Y. and Ang, B. W. (2013). Index decomposition analysis applied to CO2 emission studies. *Ecological Economics*, 93:313–329.

Xu, Y. and Dietzenbacher, E. (2014). A structural decomposition analysis of the emissions embodied in trade. *Ecological Economics*, 101:10–20.

Zhang, F. and Ang, B. (2001). Methodological issues in cross-country/region decomposition of energy and environment indicators. *Energy Economics*, 23(2):179–190.

Appendix A China and its trading partners

Group	Countries
China	Mainland China, Macao, Hong Kong
Partners (181 countries)	Afghanistan, Albania, Algeria, Andorra, Angola, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium-Luxembourg, Belize, Benin, Bermuda, Bhutan, Bolivia, Bosnia and Herzegovina, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic, Chad, Chile, Colombia, Comoros, Congo, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Democratic Republic of Congo, Djibouti, Dominica, Dominican Republic, East Timor, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Greenland, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Korea, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Liberia, Libya, Lithuania, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, Slovak Republic, Slovenia, Solomon Islands, South Africa, Spain, Sri Lanka, State of Palestine, Sudan, Suriname, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

Note: China is defined as the whole of mainland China, Macao and Hong Kong.
Source: Author.

Appendix B Other results

Table 4: Changes in EEBT, new emission creations and real emission transfers

Years	$\Delta EEBT$	Without NEE		With NEE			Change rate (%)		Products by sets		
		$\Delta Creations$	$\Delta Transfers$	$\Delta Creations$	$\Delta Transfers$	NEE	$\Delta Creations$	$\Delta Transfers$	Ex	En	So
1996	-53.85	-28.26	-25.59	-28.26	-25.59	0.25 10^3	0.79 10^3	0.11 10^3	1006	1	0
1997	1.74	0.60	1.14	0.60	1.14	-1.56 10^3	0.06	0.10	1005	0	1
1998	-45.16	-56.06	10.90	-56.06	10.90	-1.56 10^3	-0.69 10^3	0.01	1005	1	1
1999	71.21	-18.82	90.03	-18.82	90.03	-1.56 10^3	-2.04 10^3	1.31 10^3	1005	1	1
2000	-38.98	-50.50	11.52	-57.33	7.77	10.57	13.51	-32.52	1006	24	0
2001	-32.03	-52.53	20.50	-74.03	10.34	31.65	40.92	-49.54	1005	25	1
2002	-28.63	-26.44	-2.18	-29.24	-3.01	3.63	10.58	37.90	1004	25	2
2003	108.60	111.28	-2.68	111.45	-3.79	0.94	0.16	41.63	1004	24	2
2004	331.36	290.65	40.71	289.25	38.92	3.18	-0.48	-4.39	1004	25	2
2005	501.17	406.62	94.54	401.96	93.97	5.24	-1.15	-0.61	1006	27	0
2006	768.37	593.47	174.89	587.67	174.00	6.69	-0.98	-0.51	1006	25	0
2007	983.40	714.23	269.17	709.12	268.66	5.62	-0.72	-0.19	1006	26	0
2008	999.63	695.18	304.45	690.43	303.74	5.46	-0.68	-0.24	1005	25	1
2009	441.13	385.73	55.40	380.23	53.19	7.70	-1.42	-3.98	1004	25	2
2010	781.03	623.58	157.45	617.68	155.58	7.77	-0.95	-1.19	1002	26	4
2011	904.93	776.29	128.64	771.76	128.76	4.40	-0.58	0.09	1002	26	4
2012	874.34	711.16	163.18	706.84	162.91	4.59	-0.61	-0.17	1003	26	3
2013	766.04	648.70	117.35	644.55	117.17	4.32	-0.64	-0.15	1002	26	4
2014	988.12	652.96	335.16	643.80	299.26	45.07	-1.40	-10.71	1002	26	4

Note: NEE means net entry effect. Ex, En and So define respectively the set of existing, entering and exiting products. Without NEE $\Delta EEBT = \Delta Creations + \Delta Transfers$, while with NEE $\Delta EEBT = \Delta Creations + \Delta Transfers + NEE$. Rate of change of $\Delta Creations$ (respectively $\Delta Transfers$) is computed as the difference between the $\Delta Creations$ (respectively $\Delta Transfers$) obtained with NEE and that obtained without NEE divided by the $\Delta Creations$ (respectively $\Delta Transfers$) obtained without NEE. The results are in Mt (Megaton), except for the change rate, which is in percentage.
Source: Author.

Table 5: Variability around the average contribution of each effect (in %)

Years	New emission creations (%)								Real emission transfers (%)							
	Scale		B-P composition		W-P composition		Technical		Scale		B-P composition		W-P composition		Technique	
	RR	CV	RR	CV	RR	CV	RR	CV	RR	CV	RR	CV	RR	CV	RR	CV
1996	9.93	4.08	-286.35	-141.24	-133.46	-62.91	-5.91	-1.49	-35.09	-12.13	-27.33	-11.28	75.48	32.74	-116.94	-39.19
1997	21.04	9.60	-138.21	-56.35	-339.17	-149.75	-23.27	-10.37	-158.97	-57.56	232.49	113.43	-252.09	-119.30	89.95	29.43
1998	38.91	15.25	77.51	25.21	-148.93	-53.56	-20.44	-7.62	-60.07	-18.81	362.91	162.85	-732.53	-348.72	76.32	26.66
1999	69.36	24.78	-84.02	-26.05	126.83	32.64	-66.33	-24.97	109.25	46.48	332.14	113.54	150.78	64.04	183.55	48.90
2000	54.81	25.78	-192.39	-63.59	-233.91	-68.52	-48.22	-19.99	-53.77	-17.10	-431.81	-156.32	135.56	46.56	82.93	23.31
2001	62.88	29.53	-258.75	-83.17	-238.94	-68.97	-54.27	-21.78	-119.65	-35.66	224.80	79.35	-687.64	-254.57	213.36	57.29
2002	59.04	27.88	-236.63	-74.62	-323.23	-105.48	-60.34	-25.82	-288.81	-94.03	286.43	119.68	-477.13	-171.12	332.18	89.77
2003	49.10	22.31	-557.18	-189.75	-790.67	-246.65	-79.63	-34.60	-104.54	-40.38	848.42	288.65	175.29	64.60	190.56	53.50
2004	46.28	16.55	226.68	59.43	141.73	37.67	-83.71	-39.23	-320.01	-114.44	-399.65	-141.54	233.41	67.32	422.53	104.11
2005	45.14	15.08	373.34	120.37	186.08	49.58	-90.66	-43.00	-310.21	-104.92	273.76	122.29	-1275.06	-413.88	432.28	113.79
2006	51.22	15.72	326.88	96.37	215.40	58.09	-107.75	-50.47	-320.36	-134.47	923.10	230.00	202.62	68.17	1454.58	332.32
2007	63.91	19.53	421.10	129.07	237.54	63.24	-121.79	-56.30	-888.77	-300.35	8219.06	1806.70	289.88	80.14	-4284.55	-935.97
2008	72.31	21.41	509.29	155.02	225.77	59.57	-124.04	-55.88	-340.05	-131.81	228.60	92.93	340.19	118.46	2303.85	601.86
2009	83.19	24.51	549.25	176.61	195.07	50.03	-104.70	-44.96	-288.56	-111.38	-4630.26	-1191.02	301.25	92.89	920.05	234.44
2010	87.86	25.65	602.43	184.43	215.56	55.81	-125.43	-54.82	-1041.44	-312.54	-727.34	-196.99	411.71	115.81	-6643.69	-1455.69
2011	92.71	26.19	969.92	298.97	225.17	58.98	-135.58	-58.84	-457.03	-151.05	-547.87	-173.59	295.68	95.46	132.83	343.47
2012	101.73	29.20	7091.10	2240.48	250.86	65.48	-138.85	-60.86	-254.12	-114.82	-2484.59	-549.05	238.57	92.94	801.28	245.41
2013	108.78	31.61	9903.67	3015.37	264.58	68.64	-141.26	-60.68	-593.56	-186.77	-385.38	141.80	-765.36	-237.11	992.89	275.50
2014	116.56	35.69	7000.43	2108.08	289.93	75.50	-146.46	-64.67	-399.20	-158.38	-461.83	145.78	288.10	98.15	851.08	251.67

Note: RR is the range (maximum-minimum) relative to the average and CV is the coefficient of variation. $RR = ((Maximum - Minimum)/Mean) \times 100$ and $CV = (Standard\ Deviation/Mean) \times 100$. Scale effect of exports (Scale), between-partner composition effect of exports (B-P composition), within-partner composition effect of exports (W-P composition) and technical gap effect (Technical gap) are the effects related to new emission creations. Scale effect of net exports (Scale), between-partner composition effect of net exports (B-P composition), within-partner composition effect of net exports (W-P composition) and partners' technical effect (Technique) are the effects related to real emission transfers. The results are in percentage.
Source: Author.