AIR AND WATER POLLUTION OVER TIME AND INDUSTRIES WITH STOCHASTIC DOMINANCE

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Abstract. We employ a stochastic dominance (SD) approach to analyze the components that contribute to environmental degradation over time. The variables include countries' greenhouse gas (GHG) emissions and water pollution. Our approach is based on pair-wise SD tests. First, we study the dynamic progress of each separate variable over time, from 1990 to 2005, within 5-year horizons. Then, pair-wise SD tests are used to study the major industry contributors to the overall GHG emissions and water pollution at any given time, to uncover the industry which contributes the most to total emissions and water pollution. While $CO2$ emissions increased in the first-order SD sense over 15 years, water pollution increased in a second-order SD sense. Electricity and heat production were the major contributors to the $CO2$ emissions, while the food industry gradually became the major water polluting industry over time.

Keywords: environmental degradation; GHG emissions; stochastic dominance; water pollution

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1. Introduction

There are various indicators and assessment methodologies for evaluating in practice the performance of industries, cities and countries, at global, national and regional level, related to economic and environmental sustainability (see e.g. Singh et al. (2012), providing a recent overview of a great number of indicators that are already common practice for policy-making; Blanchet and Fleurbaey (2013), which favor a dimension by dimension dashboard approach; Xepapadeas and Vouvaki, 2008, Agliardi, 2011, Pinar et al., 2014, Agliardi et al., 2015, for detailed discussions of environmental sustainability). In this paper we propose a novel methodology which allows us to assess temporal trends and industry contributions to air and water pollution and to identify the cases where externalities affect the overall pollution. Our methodology is sufficiently general and data-driven, so it can be employed to alternative units and at different levels.

We examine air and water pollution that have been extensively analyzed through their linkages to economic development (Dasgupta, 2000; Persson et al., 2006; Tamazian et al., 2009; Ordás Criado et al. 2011; Sivakumar and Christakos, 2011; Xepapadeas, 2011; Li et al., 2014; Paruolo et al., 2015). Air pollution is a major concern for various environmental policies and is perceived as one of the biggest threats to human health and global warming. $CO2$ emissions, and also other greenhouse gases (GHG), affect air quality and have been identified as prime contributors. At the same time, water pollution is another major aspect of environmental degradation. Some preliminary information about these forms of environmental degradation can be obtained by pollution flow accounts. They track the generation of pollution by each industry and final demand sector. They also give data about the changes of pollution over time, to monitor the interaction between the environment and the economy and the progress toward meeting environmental protection goals.

In this paper we employ a stochastic dominance (SD) approach, which is a pretty general method allowing us to have a full picture of the environmental degradation over time and the major industry contributions to each polluting factor. It relies on pair-wise SD tests. Pair-wise SD tests are based on comparisons of cumulative distribution functions (CDFs), providing robust orderings in terms of welfare levels (e.g., Davidson and Duclos, 2000; Barrett and Donald, 2003; Anderson, 2004). Stochastic orderings are defined on classes of probability distributions and represent intuitively, in case of welfare improvements, why one population's welfare is increased more than another, irrespective of the poverty lines (Davidson and Duclos, 2000) or for all income levels (Anderson, 2004). Pair-wise SD comparisons among populations allow one to ascertain whether there is an improvement, say, in the income levels of a given population over another one, for all income groups (i.e., in all parts of the income distribution). For example, pair-wise SD is used to assess whether social programs and tax reforms improve social welfare, by analyzing the empirical distribution of income levels after and before tax reforms (see e.g., Duclos et al., 2005 and 2008). In this respect, one evaluates the income distribution across the population before and after tax reforms by looking at its CDFs (and integral of CDFs), and if the income distribution after tax reforms dominates the income distribution before tax reforms, then one could suggest that there is always a higher proportion of population with higher income levels in all parts of the income distribution. More recently, pair-wise SD tests have been used to compare male and female earnings in a competitive environment to ascertain whether one group has higher earnings at all earnings levels (Ors et al., 2013). Hence, SD tests compare the entire probability density function, rather than a finite number of moments, so SD approach can be considered less restrictive and more robust in comparisons across populations.

Although pair-wise SD comparisons are used extensively in well-being and poverty (see, e.g., Davidson and Duclos, 2000; Pinar et al., 2013), to our knowledge, only Makdissi and Wodon (2004) apply SD analysis to compare $CO2$ emissions between 1985 and 1998, and find that there has been first-order dominance up to a level, however not for all levels of $CO2$ emissions. Furthermore, they find that there has been an overall increase in emissions over a 13-year period. In this paper, we extend the SD applications, both at first-order and second-order, to different types of emissions, water pollution and different polluting industries.

Our methodology is particularly well-suited to answer questions like these: Given that GHG emissions or water pollution not only vary over time but also across industries, is there a general increase (decrease) in GHG emissions or water pollution over time? If so, which industry has been the major contributor to those increases (decreases) in GHG emissions or water pollution? One could argue that an increase (or decrease) in GHG emissions over-time could be directly ascertained by counting the average GHG emissions. However, as discussed above, SD is more informative, considering the entire CDF rather than the average only. Indeed, this increase (or decrease) might be driven by a relatively larger increase (or decrease) of emissions of some countries (yielding a reallocation of emissions from central masses towards the tails of the distribution). For the purpose of distinguishing whether the changes have to be attributed to individual units (countries, industries, etc.) or there has been an overall change affecting all units, we adopt first-order and second-order SD. First-order SD (SD1 hereafter) would reveal information whether there has been a point-wise deterioration (improvement) over time. In this respect, SD1 analyzes the marginal CDFs of the environmental degradation at all levels of GHG emissions (or water pollution) and suggests whether there has been a proportional increase (decrease) in environmental degradation in all parts of the distribution, or not. For example, if emissions from industry A first-order dominate the emissions from industry B, this would suggest that there are always higher emission levels in industry A compared to B at all levels of emissions (i.e., the proportion of countries that emit above a given emission level is always higher in industry A than B). In other words, the higher emissions in one industry are not driven by some specific countries, but they are higher at all emission levels (or, alternatively, the probability of having higher emissions above a given level in industry A is higher than in B, at all levels of emissions). Similarly, SD1 over time would suggest that there is always a higher proportion of countries that emit more above a given level over time. On the other hand, second-order SD (SD2 hereafter) would suggest that there is no point-wise deterioration (improvement), but an overall deterioration (improvement) over-time. In fact, SD2 does not analyze the CDFs, but the integrals of the CDFs (i.e., sum of environmental degradation up to a level of environmental degradation). In this case, there might not be a higher proportion of countries that emit more above a given level over time, but a higher sum of the emissions above a given level by emitters over time. In other words, some countries' pollution levels might decrease and some others might increase over time, but if the sum of the pollution above a given level is higher over time, this would suggest that there has been an overall increase in air and/or water pollution for all given levels, even though not all countries experienced an increase in their pollution levels.

SD2 is particularly important when analyzing the possible negative externalities and free-riding issues in water pollution and overall GHG emissions. Negative externalities are defined as the social costs of the market activity (e.g., consumption and production) not covered by the private cost of the activity (e.g., Dahlman, 1979). Producers make decisions based on the direct cost of production and revenues, but do not take into account the social costs of pollution (see Baumol, 1972 for detailed discussion), such as acid precipitation and global warming (Arrow et al., 2004; Rezai et al., 2012). Tol (2009) suggests that low-income countries, which contribute the least to climate change because of their low production and consumption levels, are most vulnerable to its effects, as their adaptation to climate change is limited, due to the shortcomings in resources and institutions (e.g., Smit and Wandel, 2006). Thus, even though the gains from economic activities linked with emissions are private, the costs associated with emissions are global. Therefore, it is not straightforward to identify which countries are responsible for the negative externalities of environmental degradation. In particular, $CO2$ emissions have been mainly flowing to other partner countries through international trade (Peters and Hertwich, 2008). For example, China's $CO2$ emissions have been increasing over time due to its exports to other countries (Yunfeng and Laike, 2010). Similarly, Dominguez-Faus et al. (2009) point out that water pollution increased over time due to major transportation biofuel needs across countries. Bernauer and Kuhn (2010) examine water pollution within Europe and analyze whether democracies that trade and are bound by international treaties are less likely to harm one another environmentally. They find that free-riding incentives are in place. Free-riding occurs when some users of the public good use these services without paying for them (see e.g., Gans et al., 2012). In this case, free-riding occurs when the cost of water pollution is not paid by some countries, even though they are responsible for it. Sigman (2002) found that free riding may substantially increase pollution in international rivers, whereas there is less free riding within the European Union, suggesting that international institutions might work as mitigating factors (see Sullivan, 2011 which provides a multivariate model that assesses water vulnerability).

When there is no straightforward identification of contributors to water pollution and/or GHG emissions, we can employ SD2 to account for aggregate global contribution. Some countries' direct contribution to the environmental degradation might decrease over time (e.g., due to lower production), yet their indirect contribution to the aggregate level of environmental degradation might increase due to their consumption, as their imports would lead to higher levels of GHG emissions in their trading partners. In this case, even though one cannot find an absolute increase in environmental degradation for all countries at all levels, one can evaluate the aggregate environmental degradation levels at different levels (i.e., sum of environmental degradation levels up to a given level) through SD2.

Here we implement two complementary SD approaches. Firstly, we employ consistent SD tests from Barrett and Donald (2003) to examine the dynamic progress of each separate GHG emissions (i.e., $CO2$, methane, nitrous and other greenhouse gas emissions) and water pollution over time from 1990 to 2005 within 5-year horizons. In other words, we examine whether there has been a general deterioration or improvement in each component. In that regard we will be able to obtain information on those environmental quality dimensions that are fast-moving (i.e., fast deteriorating or fast improving dimensions) or slow-moving (i.e., dimensions that remain at steady levels) for all countries over the period we analyze. Secondly, pair-wise SD tests allow us to examine the major industry contributors to the GHG emissions and water pollution at any given time. In order words, at a given time, we compare each industry contribution to GHG emissions and water pollution with all possible other industries to uncover the industry which contributes the most to total emissions and water pollution. The use of statistical tests allows us to obtain the level of statistical significance of environmental degradation (or improvement) over time.

Therefore, SD analysis provides a robust comparison of environmental degradation over time and industries, disentangles the effects of externalities, and determines the statistical significance level for such degradation. As such, it can be a useful guideline for the direction of environmental protection and public policy intervention. Fast-moving variables (in the components of GHG emissions and water pollution) provide an indication for pollution prevention, calling for the redesign of industrial processes and new technologies to reduce pollution. At the same time, they offer directions for policy instruments in the form of official restrictions and positive incentives designed to control activities that may be harmful to the quality of the environment.

This paper is organized as follows. Section 2 compares the SD method with other methods employed in the literature to evaluate spatio-temporal trends. Section 3 describes the methods and data and Section 4 discusses our results. Finally, Section 5 contains the main conclusions.

2. Comparison between Bayesian approaches and SD

In his section we discuss the advantages of the SD method over alternative Bayesian approaches which have been employed to extract the spatio-temporal trends. Bayesian approaches have been employed to analyze different types of risk assessments, such as health, environmental and burglary risks - by allowing different levels of space-time dependence (Besag et al., 1991; Waller et al., 1997; Wikle et al., 1998). Bayesian methods consider specific spatial effects, time effects, and an interaction of these two effects (with prior assumptions about their interaction) to analyze the evolution of risk over time and to estimate the posterior risk levels. In particular, Bayesian approaches have been employed to analyze the environmental risk (Wikle, 2003), where the spatio-temporal dependence is present, such as increase in PM10 pollution (Cocchi et al. 2007), rural ozone levels in the Ohio state (Sahu et al., 2007), risk of earthquake

(Natvig and Tvete, 2007), extreme precipitation (Sang and Gelfand, 2009) and extreme waves (Scotto and Guedes Soares, 2007; Vanem, 2011), among other fields. Bayesian approaches are

helpful in identifying the posterior risk by taking into account the spatial dependence; however, not only they classify risk relatively (prior choice of extreme events or risk categorization), but also they seem not to be suitable to analyse the environmental risk when there is no clear spatial dependence. In fact, Bayesian methods allocate spatial dependence a priori, estimating risk differently if space units share a common border or not. However, when dealing with environmental degradation, externalities in GHG emissions have global effects. Hence, our view is that the SD approach can be a more suitable method than the Bayesian ones, when there is no clear-cut spatial dependence. Table 1 provides a comparison between BHM and SD approach, and gives details why SD approach is more suitable in analyzing the environmental degradation data than BHM.

Table 1: Comparison between stochastic dominance (SD) and Bayesian hierarchical methods (BHM)

Bayesian hierarchical methods (BHM)	***Stochastic dominance (SD)***
Takes into account the spatial dependence, but is not suitable when there is no clear spatial dependence	Captures global dependence when a priori spatial dependence is not a reasonable assumption. SD is more suitable if environmental degradation has global consequences rather than spatial.
Takes into account the time-dependence (see, e.g., Law et al., 2014a), but time-effect is usually driven by the first two moments (mean and standard deviation of risk) only.	Takes into account the time-effect, but analyses the empirical distribution of risk (i.e., all moments), and hence provides a more robust comparison over-time and across industries
Provides posterior risk estimations; however, comparisons are usually relative to the distribution of risk in spatial units (see, e.g., Li et al., 2014; Law et al., 2014a and 2014b)	Suitable to analyse both absolute and relative risk over-time and space.
It is based on prior probabilistic assumptions on the dependent variable for posterior risk estimations (Vanem, 2011)	It is nonparametric as it does not impose any restrictions on the functional forms of probability distributions.

3. Methods and data

3.1. Pair-wise SD tests

Let us define SD pair-wise comparisons of a given variable over two points in time. In particular, we examine SD of the GHG emissions and water pollution in a 15-year and 10-year period, respectively (from 1990 to 2005 for GHG emissions, and from 1995 to 2005 for water pollution) and determine whether there has been a deterioration or improvement in each environmental quality indicator over time above a given pollution level. Additionally, SD pair-wise tests are employed for the sub-industry comparisons for GHG emissions and water pollution. In other words, we find major contributing industries to emissions and water pollution at a given time, comparing the CDFs of the pollution levels of the various industries. If there is SD1, this would suggest that degradation in one industry is clearly higher than in another at all levels of pollution. If there is no SD1, then we move to SD2 and analyze whether the sum of the pollution levels above a given pollution level is relatively higher in one industry than in another one at all levels of pollution. In particular, we apply the consistent SD tests provided by Barrett and Donald (2003).

Let us consider the pair-wise SD tests for water pollution comparisons over time. Denote by Z^1 and Z^2 the water pollution levels from two samples of countries at either two different points in time or different sub-industries at a given time. Suppose that Z^1 and Z^2 have associated cumulative distribution functions (CDFs) given by F_1 and F_2 respectively. In this context, Z^1 stochastically dominates Z^2 at the first-order if $F_1(z) \leq F_2(z)$ for all z level, where z is the environmental degradation level (e.g., water pollution level). When this occurs, the water pollution level in sample Z^1 is at least as large as that in sample Z^2, for any utility function U that is a decreasing monotonic function of z – i.e., $U'(z) \leq 0$ since the higher z (environmental degradation), the lower the utility.

How do we interpret SD1 of Z^1 (e.g., water pollution levels of countries due to activities in industry A), over Z^2 (e.g., water pollution levels of countries due to activities in industry B), i.e., $F_1(z) \leq F_2(z)$? If the CDF of pollution levels due to activities in industry A is always below the CDF of pollution levels due to activities in industry B, then the proportion of countries that pollute due to activities in industry A is always greater than that of industry B at all levels of pollution, i.e., z. Therefore, industry A stochastically dominates industry B in the first-order sense (see Fig. 2 as an example of SD1). In this respect, there is a clear ordering of industries in terms of environmental risk they impose.

If the CDF of pollution levels from one sample does not lie below the CDF of water pollution levels from the other sample at all z levels (i.e., when the two CDF curves intersect), then there is no SD1 of one industry over another, and the ordering of industries in terms of environmental risk is ambiguous. This leads to an ambiguous situation which makes it necessary to test for SD2. SD2 of Z^1 (water pollution levels due to activities in industry A) over Z^2 (water pollution levels due to activities in industry B) corresponds to $\int_0^z F_1(p)dp \leq \int_0^z F_2(p)dp$ for all z level, where p is the pollution level that takes values between 0 and z. It holds for any utility function U that is a monotonically decreasing and concave, that is, $U'(z) \leq 0$ and $U''(z) \leq 0$. The utility function is monotonically decreasing, as pollution reduces welfare, and concave, as it is expected that most policy makers would be averse to an increased dispersion of pollution. SD2 of one sample over another is tested not by comparing the CDFs themselves, but comparing the integrals below them. If the area beneath the $F_1(z)$ distribution is less than the area beneath $F_2(z)$ at all levels of z, then $F_1(z)$ stochastically dominates $F_2(z)$ in the second-order. Thus, the sum of the pollution by countries that pollute above z is always higher in industry A than in industry B.

In other words, SD2 of industry A over industry B implies that even though the proportion of countries that emit above a given pollution level is not higher in one industry than in another one, the sum of pollution is always greater in industry A than in B at all degradation levels.

We can also present the orders of SD using the integral operator, $\zeta_j(.;F)$, as a function of *F* defining SD of order *j-1*. Thus:

$$\zeta_1(z;F) := F(z),$$
$$\zeta_2(z;F) := \int_0^z F(p)dp = \int_0^z \zeta_1(p;F)dp,$$

where $\zeta_1(z;F)$ is the CDF of the population Z and $\zeta_2(z;F)$ is the integral counterpart of the CDF of the population Z.

The general hypotheses for testing SD1 of Z^1 over Z^2 (e.g., pollution levels over-time or pollution levels from different industries) with respective CDFs of $F_1(z)$ and $F_2(z)$ can be written as:

$$H_0 \ : F_1(z) \leq F_2(z) \text{ for all } z \in [0, \bar{z}],$$

$$H_1 \ : \ F_1(z) > F_2(z) \text{ for some } z \in [0, \bar{z}],$$

where the environmental degradation level, z, ranges between 0 and a finite upper level $\bar{z}$. If one fails to reject the null hypothesis, then CDF , say in industry A, is always less than in industry B, that is, the proportion of countries that pollute due to activities in industry A is always greater than the proportion in industry B at all levels of emission. If there is some degradation level z at which the dominance relation between two samples change (i.e., alternative hypothesis), then there is no clear ordering of samples compared (i.e., two CDF curves intersect at some degradation levels of z), and therefore this is no SD1 of one sample over another. Similarly, we can write the general hypotheses for testing SD2 of Z^1 over Z^2. In this case the areas under the CDF curves of two samples are compared (see section 2 of Barrett and

Donald, 2003 for asymptotic properties of the tests).

Let us assume that Z_i^1 and Z_j^2 are two samples with CDFs F_1 and F_2 respectively and the sample sizes might be different for each sample where i=1,2,...,N and j=1,2,...,M. The empirical counterparts of the distributions to construct tests are, respectively:

$$\hat{F}_1(z) = \frac{1}{N}\sum_{i=1}^{N} 1(Z_i^1 \le z), \qquad \hat{F}_2(z) = \frac{1}{M}\sum_{j=1}^{M} 1(Z_j^2 \le z), \tag{1}$$

where $1(Z_i^1 \le z)$ is an indicator function taking value of 1 if pollution level of spatial unit is less than or equal to z , and zero otherwise (Davidson and Duclos, 2000). In other words, the empirical counterparts of the distributions calculate the proportion of spatial units in each sample that has a degradation level that is less than or equal to z.

The test statistics for testing the hypotheses can be written compactly using the integration operator as follows:

$$\hat{S}_j = \left(\frac{NM}{N+M}\right)^{1/2} \sup_z \left(\zeta_j(z;\hat{F}_1) - \zeta_j(z;\hat{F}_2)\right) \tag{2}$$

for first-order (second-order) of SD when j=1 (j=2) where sup operator denotes supremum difference between CDFs (integrals of CDFs) of samples Z_i^1 and Z_j^2 at a given degradation level of z, respectively.

We finally consider tests based on the decision rule:

$$\text{reject } H_0^j \text{ if } \hat{S}_j > \mathrm{c}_\mathrm{j} \tag{3}$$

where H_0^j is the null hypothesis for first-order (second-order) dominance of Z_i^1 over Z_j^2 when j=1 (j=2) and c_j are suitably chosen critical values to be obtained by simulation methods.

To make the result operational, one needs to find an appropriate critical value c_{j} that satisfies $P(\overline{S}_j^{F_1} > \mathrm{c}_{\mathrm{j}}) \equiv \alpha$ or $P(\overline{S}_j^{F_1,F_2} > \mathrm{c}_{\mathrm{j}}) \equiv \alpha$ (some desired probability level such as 0.05 or 0.01). Since the distribution of the test statistic depends on the underlying distribution, we rely on bootstrap methods to simulate the p-values (see section 3 of Barrett and Donald, 2003 for the related bootstrapping to obtain test statistics for the hypotheses; SD tests are conducted with the use of GAUSS codes available on http://garrybarrett.com/research/).

3.2. Data

The dataset consists of different types of GHG emissions (CO_2 emissions, methane emissions, nitrous oxide emissions, and other GHG emissions) and water pollution, and their sub-industry contributions for several countries in various years, between 1990 and 2005. Although some types of pollutants have annual data and for longer periods, to keep the analysis the same for all variables, we only consider the periods where we have information for all variables. GHG emissions consist of total CO_2, methane, nitrous oxide and other GHG emissions (i.e., perfluorocarbon, hydrofluorocarbon, and sulfur hexafluoride) at a given year for a given country and the latter three emission types are measured in terms of CO_2 equivalent levels, which allow us to conduct pair-wise comparisons over time. Annual national estimates for the total fossil-fuel CO_2 emissions and respective fossil-fuel CO_2 emissions from solid (coal), liquid (oil) and gas (natural gas) consumption come from the Carbon Dioxide Information Analysis Center (CDIAC) of the U.S. Oak Ridge National Laboratory (see Boden et al., 2013). Data on carbon dioxide emissions by sector are from International Energy Agency (IEA) electronic files which are also reported in the World Bank's World Development Indicators (World Bank, 2012). Methane, nitrous oxide and other GHG emissions and their sub-industry contributions are obtained from the the European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL). Emission Database for Global Atmospheric Research (EDGAR): http://edgar.jrc.ec.europa.eu/. Finally, water pollution is measured by biochemical oxygen demand (BOD) which is the amount of oxygen that bacteria in water will consume in breaking down waste. These data are initially obtained with the methodology of Hettige et al. (2000) where end of pipe discharge of organic emissions are measured using different sector information, and updated by the World Bank's Development Research Group using the same methodology. All the data sets are categorized and taken from the World Bank's World Development Indicators (World Bank, 2012). Appendix Table A provides the list of countries used in our analysis for water pollution, total CO_2, methane, nitrous oxide and other GHG emissions. Sub-industry contributions to the water pollution and different type of emissions also cover the same countries listed under general categories. Appendix Table B offers the detailed variable definitions and sources, and provides electronic links to the data sources.

4. Results and discussion

4.1. SD comparisons in air pollution

4.1.1. CO_2 emissions

First, we present our findings from the pair-wise SD1 and SD2 comparisons of CO_2 emissions from 1990 to 2005, based on the bootstrap methods from Barrett and Donald (2003), for total, sub-industry and sub-fuel CO_2 emissions. We first perform consecutive tests, comparing total CO_2 emissions, and then CO_2 emissions from each individual sector (e.g., emissions from the electricity and heat production), for each pair of 5-year horizons between 1990 and 2005. Furthermore, we also test CO_2 emissions from different sub-fuel consumptions for each pair of 5-year horizons between 1990 and 2005. These consecutive tests allow us to analyze whether over time deteriorations (or improvements) have occurred in CO_2 emissions and, additionally, which sector and/or sub-fuel consumption is mainly responsible for such deteriorations (or improvements).

Table 2 suggests that there has been no clear SD1 and SD2 (i.e., no proportional increase or sum of aggregated environmental degradation at all risk levels) from 1990 to 2000 (i.e., SD1 and SD2 are rejected in all cases). In other words, there has been an increase in some countries' emissions and decrease in some others at some risk levels (i.e., CDF curves and their integrals for CO_2 emissions from 1990 to 2010 intersect at some risk level). However, there has been an increase in the total CO_2 emissions from 1990 to 2005, since there is dominance at first-order at the 10% significant level. Therefore, there has been a clear degradation in CO_2 emissions within 15 years by all type of emitters. Clearly, degradation here means that the proportion of countries that emits above a given emission level increased over the 15-year period of time at all emission levels, suggesting that distribution of CO_2 emissions shifted to the right at all levels. In other words, CO_2 emissions by low, medium and high emitters have increased significantly. On the other side, there has been no dominance in each sub-sector (i.e., electricity and heat production; manufacturing industries and construction; other sectors, excluding residential buildings and commercial and public services; residential buildings, commercial and public services; and the transport sector) over the whole period, suggesting that emissions in each sub-sector have been increasing for some countries, and have been decreasing for some others between 1990 and 2005. We also performed the analysis for CO_2 emissions from different sub-fuel consumptions (i.e., gaseous, solid and liquid fuel consumption). Given the space limitation, we do not present the tables, but results are available from the authors.

Table 2. Pair-wise SD comparisons of total CO2 emissions over time.

		1990	1995	2000
1995	SD1	ND	-	-
	SD2	ND	-	-
2000	SD1	ND	ND	-
	SD2	ND	ND	-
2005	SD1	10%	ND	ND
	SD2	10%	ND	ND

Notes: The vertical columns represent the years 1995 to 2005 that are tested for SD against years from 1990 to 2000. Percentage levels represent the significance level of SD. ND suggests no dominance at that order.

We find that there has been an increase in the CO_2 emissions from gaseous fuel consumption within a 15-year period (from 1990 to 2005) at all emission levels, since there is SD1 at the 5% significance level, suggesting that the emissions from gaseous fuel consumption increased for all type of emitters. Finally, we find no dominance over time from solid and liquid fuel consumption, suggesting that there is no corresponding decrease or increase in CO_2 emissions from solid and liquid fuel consumption throughout the distribution of emissions. Overall, there has been an increase in the total CO_2 emissions from 1990 to 2005 at all degradation levels, which was mostly driven by a corresponding increase in CO_2 emissions from the gaseous fuel consumption at all levels between the same periods.

Then, we study pair-wise SD comparisons by looking at CO_2 emissions from different sub-sectors in 1990, 1995, 2000 and 2005. Overall, electricity and heat production have been the most dominant sectors over the whole period for CO_2 emissions, since emissions in these industries have always been dominating all other sectors at the first-order. In other words, for given CO_2 emission level, there is always a higher proportion of countries that emits CO_2 above this level due to electricity and heat production than the proportion from other industries. This relationship holds at all CO_2 emission levels suggesting that emissions from electricity and heat production have been higher for all type of emitters. The transport sector has been the second contributor to total CO_2 emissions, since this sector significantly dominated all other sectors, except the electricity and heat production sector at the first-order. The contributions of other sectors to the CO_2 emissions are: manufacturing industries and construction; residential buildings and commercial and public services; and other sectors, excluding residential buildings and commercial and public services respectively from the highest to the lowest contributor. The significance level of the dominance of each sector on the other has been different at different periods, showing a robust ranking of sectors. (Results are available upon request from the authors).

Table 3. Pair-wise SD comparisons of CO_2 emissions from sub-fuel consumption

	a)Sub-fuel comparisons in 1990		
Industry comparisons	Dominance Outcome	SD1	SD2
GAS versus LIQUID	LIQUID dominates	1%	1%
GAS versus SOLID	SOLID dominates	ND	10%
LIQUID versus SOLID	LIQUID dominates	1%	1%
	b)Sub-fuel comparisons in 1995		
Industry comparisons	Dominance Outcome	SD1	SD2
GAS versus LIQUID	LIQUID dominates	1%	1%
GAS versus SOLID	ND	ND	ND
LIQUID versus SOLID	LIQUID dominates	1%	1%
	c)Sub-fuel comparisons in 2000		
Industry comparisons	Dominance Outcome	SD1	SD2
GAS versus LIQUID	LIQUID dominates	1%	1%
GAS versus SOLID	ND	ND	ND
LIQUID versus SOLID	LIQUID dominates	1%	1%
	d)Sub-fuel comparisons in 2005		
Industry comparisons	Dominance Outcome	SD1	SD2
GAS versus LIQUID	LIQUID dominates	1%	1%
GAS versus SOLID	SOLID dominates	ND	10%
LIQUID versus SOLID	LIQUID dominates	1%	1%

Notes: Industry comparisons columns represent all possible sub-industry comparisons at a given year. Dominance Outcome column offers the dominating sub-fuel as a result of comparisons between different sub-fuels. SD1 and SD2 represent the significance levels for the first- and second-order dominance. ND suggests no dominance at that order.

Finally, a comparison among CO_2 emissions from different types of fuel consumption from 1990 to 2005 (see Table 3) suggests that over the whole period the liquid fuel consumption has always been the major contributor to CO_2 emissions since CO_2 emissions from this type dominate the emissions from the gaseous and solid fuel consumption at first-order, at 1% significance level. On the other hand, CO_2 emissions from the solid fuel consumption dominate the emissions from the gaseous fuel consumption at the second-order, at 10% significance level in 1990 and 2005, but the relationship between these two types of fuel consumption is ambiguous in 1995 and 2000.

4.1.2. Methane emissions

We then investigate the evolution of total methane emissions, methane emissions from agriculture and the energy sector, respectively, between 1990 and 2005. The findings suggest that there has been no general increase or decrease in total methane emissions over the whole period. Similarly, no general progress of methane emissions from different sub-sectors is found between the same periods. Fig. 1 presents the CDF of methane emissions for 1990, 1995, 2000 and 2005. Clearly, the CDF curves of methane emissions for different years overlap at almost all emission levels and there is no clear dominance at any order. Fig. 2 depicts the CDFs of methane emissions released by countries due to the activities in agriculture and energy sectors in 2005. Since the CDF of the methane emissions released due to the activities in agriculture sector is always below the CDF of the methane emissions released due to the activities in the energy sector, this suggests a clear SD1 of the agriculture sector over the energy sector. In other words, there is always a higher proportion of countries that emit methane gasses to the atmosphere due to the activities taking place in the agriculture sector than in the energy sector at all emission levels. Since there is a clear ordering of industries that contribute to the methane gas emissions, one could suggest a global action plan to reduce methane emissions released by the agriculture sector. It is not that different countries emit higher levels of methane emissions in different sectors (hence country-specific actions are required), but agriculture sectors' contribution is always higher than that of energy sector and therefore a global action targeting ways to eliminate methane emissions by agriculture sectors would be a more effective strategy.

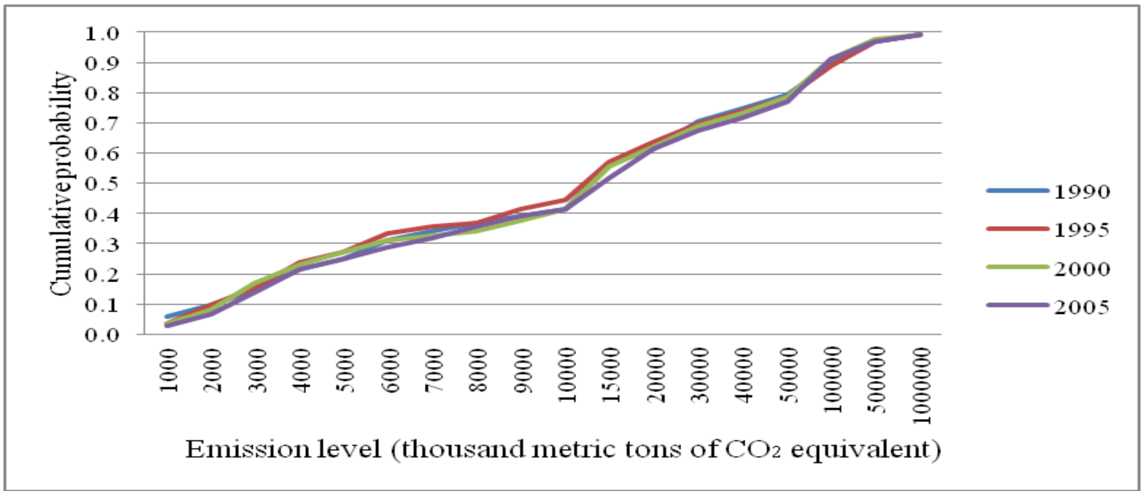

Fig. 1. Cumulative distribution functions of methane emissions in 1990, 1995, 2000 and 2005

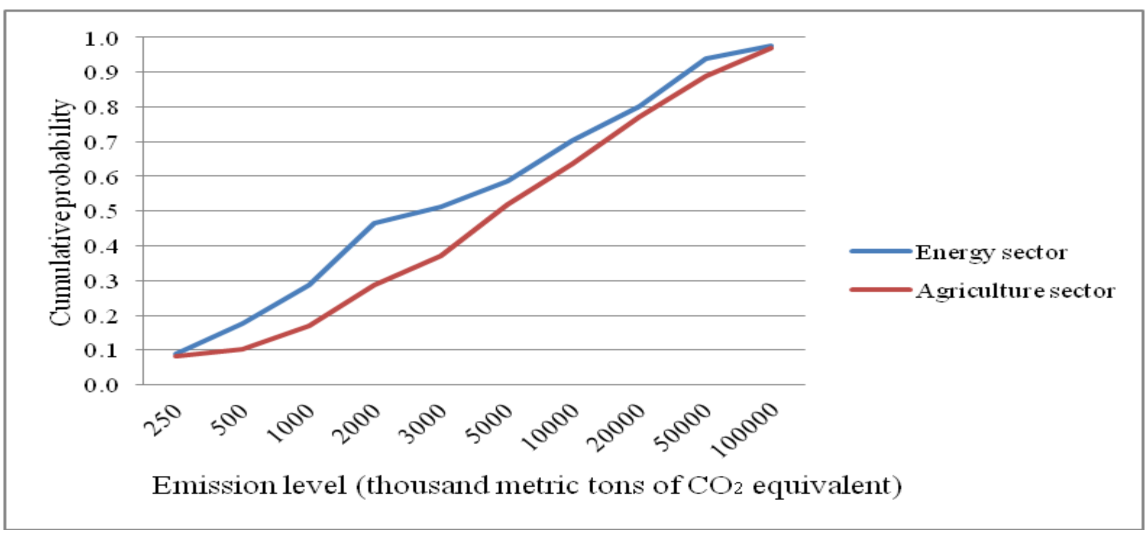

Fig. 2. Cumulative distribution functions of methane emissions from agriculture and energy sector for 2005

We also conduct the pair-wise comparisons of methane emissions from the agriculture and the energy sectors in 1990, 1995, 2000 and 2005 (Results are available upon request from the authors). For the whole period, methane emissions from the agriculture sector have always been higher than from the energy sector. Methane emissions from agriculture dominate the energy sector at the first-order at 1% significance level. Thus, for any given methane emission level, there have been always more countries emitting above that level in the agriculture sector than the energy sector. Therefore, there has been a clear robust ranking of sectors (from the highest methane emitting sector to the lowest one) over the period 1990-2005.

4.1.3. Nitrous oxide emissions

We further analyze the progress of total nitrous oxide emissions, nitrous oxide emissions from the agriculture, the industrial and the energy sectors between 1990 and 2005 (Results are available from the authors). The findings suggest that there has been neither a general increase or decrease in total nitrous oxide emissions nor the nitrous oxide emissions from different sub-sectors over time. This suggests that some countries' nitrous oxide emission levels increased and some other countries' emissions were decreased. Furthermore, increase in nitrous oxide emission levels for some countries was offset by the decrease in emissions by other countries (i.e., there was no second-order SD). In other words, country-specific (or group of country-specific) policies will be more suitable to decrease the nitrous oxide emission levels as there is no clear increase in emissions for all type of emitters.

Similarly to the analyses above, we employ the pair-wise comparisons between three sub-sectors (i.e., agricultural, industrial and energy sectors) to find the major industry which releases the highest nitrous oxide emissions over time. For the whole period, nitrous oxide emissions from the agriculture sector has always been higher than the other two sectors, while nitrous oxide emissions from the energy sector have always been higher than the industrial sector for the whole period. Nitrous oxide emissions from agriculture dominate the energy and the industrial sectors at first-order at 1% significance level and, similarly, emissions from the energy sector dominate those of the industrial sector at first-order at a significance level of 1% over the whole period. In other words, for any given nitrous oxide emission level, there have been always more countries emitting above that level in agriculture sector than the energy and industrial sector. Overall, there has been a clear robust ranking of sectors (from the highest nitrous emitting sector to the lowest one) over the period 1990-2005.

4.1.4. Other GHG emissions

Although the other GHG emissions have always been contributing less to the total, we still conduct pair-wise SD comparisons for the other GHG emissions and its sub-components from 1990 to 2005. The four panels of Table 4 present the results for the evolution of the total other GHG emissions, perfluorocarbon (PFC), hydrofluorocarbon (HFC), and sulfur hexafluoride (SF6) emissions respectively between 1990 and 2005. HFC emissions are mostly due to use of refrigeration, air-conditioning, and insulating foam products (see e.g., Velders et al., 2009). PFC emissions are mainly due to aluminum production (see e.g., Marks et al., 2013), whereas SF6 emissions are due to leakage and venting from the electricity sector, magnesium production, and other minor contributions (see e.g., Olivier et al., 2005).

Table 4. Pair-wise SD comparisons other GHG, HFC, PFC and SF6 emissions over time

a)Total other GHG emissions					*b)HFC emissions*				
		1990	1995	2000			1990	1995	2000
1995	SD1	1%	-	-	1995	SD1	1%	-	-
	SD2	1%	-	-		SD2	1%	-	-
2000	SD1	1%	5%	-	2000	SD1	1%	1%	-
	SD2	1%	5%	-		SD2	1%	1%	-
2005	SD1	1%	1%	ND	2005	SD1	1%	1%	1%
	SD2	1%	1%	ND		SD2	1%	1%	1%
c)PFC emissions					*d)SF6 emissions*				
		1995	2000	2005			1990	1995	2000
1990	SD1	5%	ND	1%	1995	SD1	ND	-	-
	SD2	5%	ND	1%		SD2	ND	-	-
1995	SD1	-	ND	ND	2000	SD1	ND	ND	-
	SD2	-	ND	ND		SD2	ND	ND	-
2000	SD1	-	-	ND	2005	SD1	ND	ND	ND
	SD2	-	-	ND		SD2	ND	ND	ND

Notes: The vertical columns represent the years 1995 to 2005 that are tested for SD against years from 1990 to 2000. Percentage levels give the significance level of SD. The vertical and horizontal axes are reversed for PFC emissions to represent the improvement over time. ND suggests no dominance at that order.

We conduct our analysis for each type of emission and find that there has been a general increase in the total GHG emissions in 5-year horizons between 1990 and 2000 suggesting that there is always a higher proportion of countries that emit above a given level in 2000 than in 1990 for all emission levels, yet no clear indication was detected between 2000 and 2005 suggesting that increase in other GHG emission by some countries was offset by a decrease in other GHG emissions by some other countries. On the other hand, HFC emissions have been increasing in 5-year horizons over the whole period as the later 5-year HFC emissions dominate the earlier ones at first-order at the 1% significance level supporting the fact that increased demand for refrigeration, air-conditioning, and insulating foam products (i.e., main contributors of the HFC emissions) and this has been the case for all type of emitters as there is always a higher proportion of countries that emit above a given HFC emission level in the following period than the previous one. On the other hand, we find no clear result for the SF6 emissions, since SD tests provide no dominance in the period as a whole. More interestingly, we find that there has been a general decrease of the PFC emissions from 1990 to 1995 and from 1990 to 2005. In other words, PFC emissions in 1990 dominate the PFC emissions in 1995 and 2005 at first-order at the 5% and 1% significance levels respectively. For PFC emissions, years on the vertical axis are tested against the horizontal but the years 1990 to 2000 are tested against the years 1995 and 2005 respectively. Since there has been a proportional decrease in PFC emissions at all emission levels over time, the testing horizon is reversed. Hence, for any given PFC emission level, there have been always more countries emitting above that level in 1990 when compared with 1995 and 2005. This confirms that there have been good adaptation strategies across the globe in reducing PFC emissions over time.

4.1.5. Comparison among GHG emissions

Finally, we performed the pair-wise SD comparisons among CO_2, methane, nitrous oxide and other GHG emissions in 1990, 1995, 2000 and 2005 (Results are available upon request from the authors). Our findings suggest a clear difference between the types of emissions. CO_2 has always been the main component that has been releasing emissions when compared with the other type of greenhouse gases. As a result, for any given CO_2 equivalent emission level, there have been always more countries emitting CO_2 above that level when compared with methane, nitrous oxide and other GHG emissions. Furthermore, methane emissions dominate the nitrous and other GHG emissions between 1990 and 2005 at first order at the 1% significance level making it the second major GHG emissions contributor. Similarly, for any given CO_2 equivalent emission level, there have always been more countries emitting methane above that level when compared with nitrous oxide and other GHG emissions. Finally, other GHG emissions (i.e., sum of the HFC, PFC and SF6 emissions), have been contributing the least, when compared with the other type of greenhouse gases. This result can help identify policies for achieving improvements in environmental quality. The implication here is that policies aiming to reduce CO_2 emissions need to be given priority when compared with the other types of emissions.

4.2. SD comparisons in water pollution

For water pollution the sample period consists only of a 10-year horizon (from 1995 to 2005). There has been information on water pollution in 1990 for only 12 countries, which makes the application impossible before 1995 since the power of tests would not be reliable. The eight panels of Table 4 give the pair-wise SD test results for the evolution of total water pollution and its sub-industries' contributors over time. The first panel of Table 5 suggests that there was no general increase in water pollution over the whole period. However, there has been an increase in water pollution in the 10-year horizon in a second-order sense, suggesting that sum of water pollution above a given level is higher in 2005 than in 1995 for all levels of pollution. Hence the sum of water pollution up to a given pollution level has always been higher in 2005 than in 1995 (i.e., some countries' water pollution decreased, but some others experienced an increase in their water pollution, and the sum of the increases in water pollution has been higher than the sum of the decreases for a given level of pollution). Fig. 3 depicts the CDFs of the water pollutant emissions (measured as BOD levels per day) for 1995, 2000 and 2005. As the CDF curves of each year intersect with each other, the tests did not yield any SD1. However, when CDFs intersect, one could test whether there is any clear ordering over time when the integrals of water pollution at each respective year (i.e., sum of the total water pollution up to a water pollution level) are compared. In this case, water pollution in 2005 dominates the water pollution in 1995 in the second-order sense at the 10% significance level. The CDFs of water pollution in

1995 and 2005 do intersect at some point (i.e., no SD1), and yet one can discover that the sum of the water pollution up to a given level is always lower in 2005 than in 1995, suggesting SD2, where the sum of water pollution above a given level is always higher in 2005 than in 1995 for all emission levels.

Table 5. Pair-wise SD comparisons of total and sub-industry water pollution over time

a)Total water pollution				*b)Water pollution from chemistry industry*			
		1995	2000			1995	2000
2000	SD1	ND	ND	2000	SD1	ND	ND
	SD2	ND	ND		SD2	10%	ND
2005	SD1	ND	ND	2005	SD1	ND	ND
	SD2	10%	ND		SD2	10%	ND
c)Water pollution from clay and glass industry				*d)Water pollution from food industry*			
		1995	2000			1995	2000
2000	SD1	ND	ND	2000	SD1	ND	ND
	SD2	ND	ND		SD2	10%	ND
2005	SD1	ND	ND	2005	SD1	ND	ND
	SD2	10%	ND		SD2	5%	ND
e)Water pollution from metal industry				*f)Water pollution from paper and pulp industry*			
		1995	2000			1995	2000
2000	SD1	ND	ND	2000	SD1	ND	ND
	SD2	ND	ND		SD2	ND	ND
2005	SD1	ND	ND	2005	SD1	ND	ND
	SD2	10%	ND		SD2	ND	ND
g)Water pollution from textile industry				*h)Water pollution from wood industry*			
		1995	2000			1995	2000
2000	SD1	ND	ND	2000	SD1	ND	ND
	SD2	ND	ND		SD2	10%	ND
2005	SD1	ND	ND	2005	SD1	ND	ND
	SD2	ND	ND		SD2	5%	ND

Notes: The vertical columns represent the years 2000 and 2005 that are tested for SD against years from 1995 and 2000. Percentage levels represent the significance level of SD. ND suggests no dominance at that order.

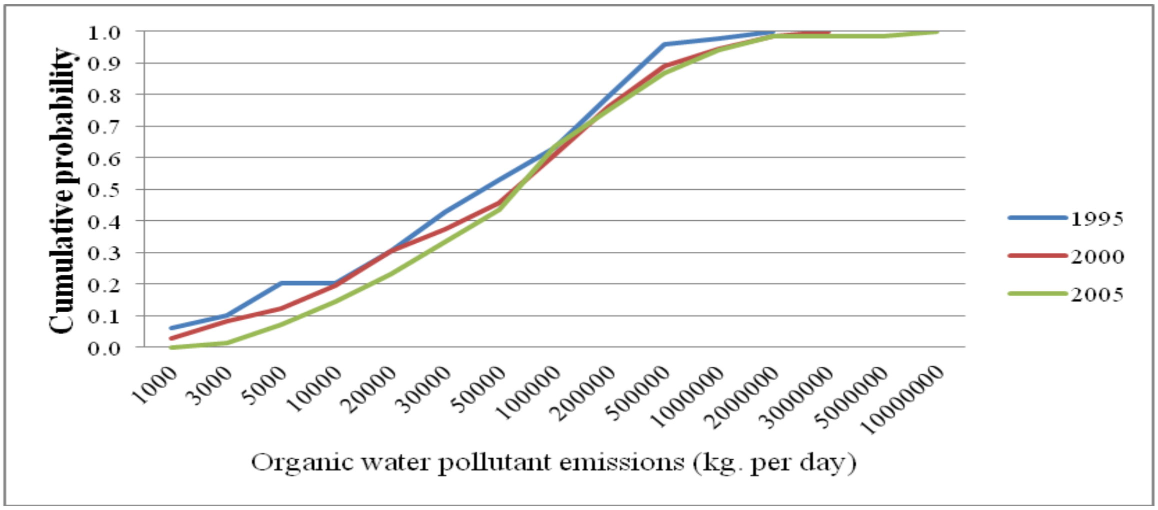

Fig. 3. Cumulative distribution functions of water pollutant emissions for 1995, 2000 and 2005

Similarly to total water pollution, there has been no improvement or deterioration in sub-industry water pollution over the whole period at all emission levels, since there has been no dominance in the first-order sense for all industries. However, water pollution levels from different industries have shown different progress over time. The sum of water pollution from chemical, food and wood industries above a given level is always higher in 2000 than in 1995 suggesting that even though some countries' water pollution in these industries decreased, increase in water pollution by some other countries were relatively more than the decrease in those countries. Furthermore, water pollution from the chemical, food, wood, metal, and clay and glass industries increased between 1995 and 2005 in the second-order sense suggesting a similar trend as above but within 10-year horizon. Finally, no dominance of any order is found for textile and paper and pulp industries. Therefore, one can conclude that the increase in water pollution over time is mostly driven by the chemical, food and wood industries as those industries experienced an overall increase of water pollution in shorter horizons (i.e., an overall increase within 5-year horizons) suggesting that the global action to reduce water pollution in these industries should be prioritized.

Finally, we analyze the sub-industry contributions to the water pollution in 1995, 2000 and 2005. The three panels of Table 6 present all possible pair-wise comparisons between sub-industry water pollutions in 1995, 2000 and 2005 respectively. In 1995 the chemical industry pollutes water more than the clay and glass, metal and wood industries (i.e., in the first panel of Table 5, chemical industry water pollution stochastically dominates the clay and glass metal and wood industries in the first-order sense at the 10%, 5% and 1% significance level respectively). Furthermore, water pollution from food and textile industries has been more than pollution from the clay and glass, metal, paper and wood industries at any pollution level in 1995. Finally, in 1995, the clay and glass industry was responsible for water pollution more than the metal industry and paper industry polluted more than the wood industry. Any further comparisons have not suggested any further dominance. Clearly, in 1995, chemical, textile and food industries were the major contributors to water pollution, as at any pollution level there have always been more countries in those industries polluting water than remaining industries above that any given pollution level.

In 2000 the majority of the dominance relations between industries remain the same, with some differences with respect to 1995. Water pollution from the food industry dominates pollution from the chemical industry in the first-order sense at the 5% significance level. In 2000 the major contributors to water pollution are the food and textile industries. However, there is no clear SD ordering among food and textile industries, when water pollution is considered. Finally, in 2005, water pollution from the food industry contributes more than any other industry (i.e., water pollution from the food industry dominates such pollution from any industry in the first-order sense). Therefore, a global action tackling the increase in water pollution due to activities in the food industry should be prioritized.

Table 6. Pair-wise SD comparison of water pollution from industries									
	Water pollution industry comparisons in 1995			Water pollution industry comparisons in 2000			Water pollution industry comparisons in 2005		
Industry comparisons	Dominating industry	SD1	SD2	Dominating industry	SD1	SD2	Dominating industry	SD1	SD2
Chemical vs. Clay	Chemical	10%	5%	Chemical	10%	5%	Chemical	5%	5%
Chemical vs. Food	ND	ND	ND	Food	5%	5%	Food	5%	5%
Chemical vs. Metal	Chemical	10%	5%	Chemical	5%	5%	Chemical	1%	1%
Chemical vs. Paper	ND	ND	ND	ND	ND	ND	Chemical	10%	10%
Chemical vs. Textile	ND	ND	ND	ND	ND	ND	ND	ND	ND
Chemical vs. Wood	Chemical	1%	1%	Chemical	1%	1%	Chemical	1%	1%
Clay versus Food	Food	1%	1%	Food	1%	1%	Food	1%	1%
Clay versus Metal	Clay	10%	10%	Clay	10%	10%	Clay	10%	10%
Clay versus Paper	ND	ND	ND	ND	ND	ND	ND	ND	ND
Clay versus Textile	Textile	10%	1%	Textile	5%	1%	Textile	5%	5%
Clay versus Wood	ND	ND	ND	ND	ND	ND	ND	ND	ND
Food versus Metal	Food	1%	1%	Food	1%	1%	Food	1%	1%
Food versus Paper	Food	10%	5%	Food	1%	1%	Food	1%	1%
Food versus Textile	ND	ND	ND	ND	ND	ND	Food	10%	10%
Food versus Wood	Food	1%	1%	Food	1%	1%	Food	1%	1%
Metal versus Paper	ND			Paper	10%	10%	Paper	10%	10%
Metal versus Textile	Textile	1%	1%	Textile	1%	1%	Textile	1%	1%
Metal versus Wood	ND	ND	ND	ND	ND	ND	ND	ND	ND
Paper versus Textile	Textile	10%	5%	Textile	5%	5%	Textile	10%	10%
Paper versus Wood	Paper	5%	5%	Paper	ND	10%	Paper	10%	10%
Textile versus Wood	Textile	1%	1%	Textile	1%	1%	Textile	1%	1%

Notes: First column represents all possible sub-industry water pollution comparisons. Second to fourth panels present the dominance outcomes between sub-industry comparisons for each respective case for the years 1995, 2000 and 2005 respectively. SD1 and SD2 represent the significance levels for the first- and second-order dominance. ND suggests no dominance at that order.

5. Conclusions

Our methodology based on consistent pair-wise SD tests can provide useful information to policy makers in their efforts to design policies that compare the risks from environmental degradation. Reducing CO_2 emissions needs to be given a priority, with special attention to those industrial sectors which are mainly responsible for these emissions. As the agriculture sector is the major contributor to the methane emissions and the food sector is becoming the industry that is polluting water the most, our findings suggest interlinkages between air and water pollution.

Water pollution will likely be intensified by the increasing demand for biomass-derived fuels for transportation biofuel needs, because large quantities of water are needed to grow the fuel crops, and water pollution is exacerbated by agricultural drainage containing fertilizers, pesticides, and sediment. Potentially, there are major spillovers in environmental degradation across countries, and across air and water pollution levels. As Olmstead (2010) claims, water pollution in transboundary settings is still a challenge since our analysis find an aggregate increase in water pollution even though some countries pollute less over time as relatively lower levels of water pollution in these countries could be due to free-riding. In other words, even though some countries' direct contribution to water pollution is decreased (due to their production levels), their indirect contribution (i.e., due to increased consumption) might have led to an aggregate increase in water pollution levels.

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Appendix Table A: List of countries used in each respective analysis

Country Name	Country Code	Water pollution	$CO2$ emissions	Methane, nitrous oxide and other GHG emissions
Afghanistan	AFG		x	
Albania	ALB	x	x	x
Algeria	DZA		x	x
Andorra	ADO		x	
Angola	AGO		x	x
Antigua and Barbuda	ATG		x	
Argentina	ARG	x	x	x
Armenia	ARM		x	x
Aruba	ABW	x	x	
Australia	AUS		x	x
Austria	AUT	x	x	x
Azerbaijan	AZE	x	x	x
Bahamas, The	BHS	x	x	
Bahrain	BHR		x	x
Bangladesh	BGD	x	x	x
Barbados	BRB		x	
Belarus	BLR		x	x
Belgium	BEL	x	x	x
Belize	BLZ		x	
Benin	BEN		x	x
Bermuda	BMU		x	
Bhutan	BTN		x	
Bolivia	BOL	x	x	x
Bosnia and Herzegovina	BIH		x	x
Botswana	BWA	x	x	x
Brazil	BRA		x	x
Brunei Darussalam	BRN		x	x
Bulgaria	BGR	x	x	x
Burkina Faso	BFA		x	
Burundi	BDI		x	
Cambodia	KHM	x	x	x
Cameroon	CMR		x	x
Canada	CAN	x	x	x
Cape Verde	CPV		x	
Cayman Islands	CYM		x	
Central African Republic	CAF		x	
Chad	TCD		x	
Chile	CHL	x	x	x
China	CHN	x	x	x
Colombia	COL	x	x	x

Comoros	COM		x	
Congo, Dem. Rep.	ZAR		x	x
Congo, Rep.	COG		x	x
Costa Rica	CRI		x	x
Cote d'Ivoire	CIV		x	x
Croatia	HRV	x	x	x
Cuba	CUB		x	x
Cyprus	CYP	x	x	x
Czech Republic	CZE	x	x	x
Denmark	DNK	x	x	x
Djibouti	DJI		x	
Dominica	DMA		x	
Dominican Republic	DOM		x	x
Ecuador	ECU	x	x	x
Egypt, Arab Rep.	EGY		x	x
El Salvador	SLV		x	x
Equatorial Guinea	GNQ		x	
Eritrea	ERI	x	x	x
Estonia	EST	x	x	x
Ethiopia	ETH	x	x	x
Faeroe Islands	FRO		x	
Fiji	FJI		x	
Finland	FIN	x	x	x
France	FRA	x	x	x
French Polynesia	PYF		x	
Gabon	GAB		x	x
Gambia, The	GMB	x	x	
Georgia	GEO		x	x
Germany	DEU	x	x	x
Ghana	GHA		x	x
Gibraltar	GIB		x	x
Greece	GRC	x	x	x
Greenland	GRL		x	
Grenada	GRD		x	
Guatemala	GTM		x	x
Guinea	GIN		x	
Guinea-Bissau	GNB		x	
Guyana	GUY		x	
Haiti	HTI	x	x	x
Honduras	HND		x	x
Hong Kong SAR, China	HKG		x	x
Hungary	HUN	x	x	x
Iceland	ISL		x	x

India	IND		x	x
Indonesia	IDN	x	x	x
Iran, Islamic Rep.	IRN	x	x	x
Iraq	IRQ		x	x
Ireland	IRL	x	x	x
Israel	ISR	x	x	x
Italy	ITA	x	x	x
Jamaica	JAM		x	x
Japan	JPN	x	x	x
Jordan	JOR	x	x	x
Kazakhstan	KAZ	x	x	x
Kenya	KEN		x	x
Kiribati	KIR		x	
Korea, Dem. Rep.	PRK		x	x
Korea, Rep.	KOR	x	x	x
Kuwait	KWT		x	x
Kyrgyz Republic	KGZ	x	x	x
Lao PDR	LAO		x	
Latvia	LVA	x	x	x
Lebanon	LBN		x	x
Lesotho	LSO	x		
Liberia	LBR		x	
Libya	LBY		x	x
Lithuania	LTU	x	x	x
Luxembourg	LUX	x	x	x
Macao SAR, China	MAC		x	
Macedonia, FYR	MKD	x	x	x
Madagascar	MDG	x	x	
Malawi	MWI	x	x	
Malaysia	MYS	x	x	x
Maldives	MDV		x	
Mali	MLI		x	
Malta	MLT	x	x	x
Marshall Islands	MHL		x	
Mauritania	MRT		x	
Mauritius	MUS	x	x	
Mexico	MEX		x	x
Micronesia, Fed. Sts.	FSM		x	
Moldova	MDA	x	x	x
Mongolia	MNG	x	x	x
Montenegro	MNE		x	
Morocco	MAR	x	x	x
Mozambique	MOZ		x	x

Myanmar	MMR		x	x
Namibia	NAM		x	x
Nepal	NPL		x	x
Netherlands	NLD	x	x	x
New Caledonia	NCL		x	
New Zealand	NZL	x	x	x
Nicaragua	NIC		x	x
Niger	NER		x	
Nigeria	NGA		x	x
Norway	NOR	x	x	x
Oman	OMN	x	x	x
Pakistan	PAK		x	x
Palau	PLW		x	
Panama	PAN	x	x	x
Papua New Guinea	PNG		x	
Paraguay	PRY	x	x	x
Peru	PER		x	x
Philippines	PHL	x	x	x
Poland	POL	x	x	x
Portugal	PRT	x	x	x
Qatar	QAT	x	x	x
Romania	ROM	x	x	x
Russian Federation	RUS	x	x	x
Rwanda	RWA		x	
Samoa	WSM		x	
Sao Tome and Principe	STP		x	
Saudi Arabia	SAU		x	x
Senegal	SEN	x	x	x
Serbia	SRB		x	x
Seychelles	SYC		x	
Sierra Leone	SLE		x	
Singapore	SGP	x	x	x
Slovak Republic	SVK	x	x	x
Slovenia	SVN	x	x	x
Solomon Islands	SLB		x	
Somalia	SOM		x	
South Africa	ZAF	x	x	x
Spain	ESP	x	x	x
Sri Lanka	LKA		x	x
St. Kitts and Nevis	KNA		x	
St. Lucia	LCA		x	
St. Vincent and the Grenadines	VCT		x	

Sudan	SDN		x	x
Suriname	SUR		x	
Swaziland	SWZ		x	
Sweden	SWE	x	x	x
Switzerland	CHE		x	x
Syrian Arab Republic	SYR	x	x	x
Tajikistan	TJK	x	x	x
Tanzania	TZA	x	x	x
Thailand	THA	x	x	x
Timor-Leste	TMP		x	
Togo	TGO		x	x
Tonga	TON	x	x	
Trinidad and Tobago	TTO	x	x	x
Tunisia	TUN		x	x
Turkey	TUR	x	x	x
Turkmenistan	TKM		x	x
Turks and Caicos Islands	TCA		x	
Uganda	UGA	x	x	
Ukraine	UKR	x	x	x
United Arab Emirates	ARE		x	x
United Kingdom	GBR	x	x	x
United States	USA	x	x	x
Uruguay	URY		x	x
Uzbekistan	UZB		x	x
Vanuatu	VUT		x	
Venezuela, RB	VEN		x	x
Vietnam	VNM	x	x	x
West Bank and Gaza	WBG		x	
Yemen, Rep.	YEM	x	x	x
Zambia	ZMB		x	x
Zimbabwe	ZWE		x	x

Appendix Table B: Variable definitions and sources

Variable	Definition and sources
*CO*2 emissions, emissions from different consumption types and emissions by sectors.	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. Detailed data set is obtained from the Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory, Tennessee, United States. The data set can be accessed from: http://cdiac.ornl.gov/. All emission estimates are expressed in thousand metric tons of carbon, where total emissions and emissions from different types of consumptions can be accessed: http://cdiac.ornl.gov/ftp/ndp030/nation.1751_2011.ems. Data on carbon dioxide emissions by sector are from IEA electronic files: http://www.iea.org/stats/index.asp which are also reported from the World Bank's World Development Indicators (World Bank, 2012) can be accessed from http://data.worldbank.org/data-catalog/world-development-indicators/wdi-2012
Methane emissions (thousand metric tons of CO2 equivalent) and sub-sector contributions	Methane emissions are those stemming from human activities such as agriculture and from industrial methane production. Total methane emissions and sector contributions to methane emission can be accessed from the European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL). Emission Database for Global Atmospheric Research (EDGAR): http://edgar.jrc.ec.europa.eu/ or http://edgar.jrc.ec.europa.eu/overview.php?v=42 which can be also accessed from can be accessed from http://data.worldbank.org/indicator/
Nitrous oxide emissions (thousand metric tons of CO2 equivalent) and sub-sector contributions	Nitrous oxide emissions are emissions from agricultural biomass burning, industrial activities, and livestock management. Nitrous oxide emissions and sector contributions to nitrous oxide emissions can be accessed from the European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL). Emission Database for Global Atmospheric Research (EDGAR): http://edgar.jrc.ec.europa.eu/ or http://edgar.jrc.ec.europa.eu/overview.php?v=42 can be also accessed from can be accessed from http://data.worldbank.org/indicator/
Other greenhouse gas emissions: perfluorocarbon (PFC), hydrofluorocarbon (HFC), and sulfur hexafluoride (SF6) (thousand metric tons of CO2 equivalent)	HFC emissions are mostly due to use of refrigeration, air-conditioning, and insulating foam products. PFC emissions are mainly due to aluminum production and SF6 emissions are due to leakage and venting from the electricity sector, magnesium production, and other minor contributions, which can be accessed from the European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL). Emission Database for Global Atmospheric Research (EDGAR): http://edgar.jrc.ec.europa.eu/ or http://edgar.jrc.ec.europa.eu/overview.php?v=42 can be also accessed from can be accessed from http://data.worldbank.org/indicator/
Water pollution and sector contributions	It is measured by biochemical oxygen demand (BOD) which is the amount of oxygen that bacteria in water will consume in breaking down waste. All the data sets are categorized and taken from the World Bank's World Development Indicators (World Bank, 2012). Industry shares of emissions of organic water pollutants are emissions from manufacturing activities as defined by two-digit divisions of the International Standard Industrial Classification revision 3. The detailed data on water pollution could be accessed through http://data.worldbank.org/data-catalog/world-development-indicators/wdi-2012