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A NEW INDEX OF ENVIRONMENTAL QUALITY BASED ON GREENHOUSE GAS EMISSIONS

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Abstract

A weighting scheme is proposed to construct a new index of environmental quality based on greenhouse gas (GHG) emissions for different countries using an approach that relies on consistent tests for stochastic dominance (SD) efficiency. The benchmark is an index that is based on the average actual contributions of the respective GHG emission types to the total. Our index stochastically dominates the chosen benchmark and allows us to figure out the "worst" and "best" case scenarios, where environmental degradation is at its maximum and minimum, respectively. If a common global action were to be taken by all countries involved, these scenarios would correspond to the most and least effective possible actions, respectively, that could be undertaken when compared to the benchmark. Then, countries are ranked and their rankings are compared with alternative rankings (e.g., the Kyoto Protocol, Annex I, and the Environmental Sustainability Index, ESI). The test statistics and the estimators are computed using mixed integer programming methods. Then, employing a complementary SD approach, pairwise SD tests are employed to examine the dynamic progress of each separate GHG emission (i.e.,CO_2, methane, nitrous oxide, and other GHG emissions) over time, from 1990 to 2005, within 5-year horizons. Pairwise SD tests are used to examine the major industry contributors to the GHG emissions at any given time and to uncover the industry which contributes the most to total emissions.

JEL Classifications: C4, C5, C14, Q01, Q5, Q51

Key Words: Environmental Quality, Emissions, Nonparametric Stochastic Dominance, Mixed Integer Programming.

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1 Introduction

Over the last few years there has been a vigorous debate about the sustainability of economic growth for many countries because of the depletion in stocks of natural resources and the deterioration in the quality of environmental services (see, for example, Arrow *et al.*, 2004; Millennium Ecosystems Assessment, 2005; World Bank, 2010; Agliardi, 2011; Arrow *et al.*, 2012), and all this is exacerbated by high population growth rates. In this paper we focus on the environmental quality of a country and construct a new index based on greenhouse gas (GHG) emissions. In particular, an optimal weighting scheme is proposed to construct the index, using an approach that relies on consistent tests for stochastic dominance efficiency. Our framework yields an empirically implementable measure that can be applied to different countries and to cross-country comparisons.

There are already some indicators and descriptive statistics in environmental accounts.[1] The environmentally adjusted net domestic product (eaNDP) is obtained by combining the conventional NDP with monetary values of environmental degradation (Repetto *et al.*, 1989). From national accounting matrix including environmental accounts (NAMEA) single indicators are obtained for different themes (acidification of the atmosphere, eutrophication of waters, etc.) by aggregating the emissions, using some common measurement unit and then comparing them with a national target level. A single-valued indicator of total material requirements (TMR) can be derived from the system of national accounts (SNA), which sums all the material use in the economy by weights, to measure dematerialization. Many researchers have criticized eaNDP for mixing actual transactions with hypothetical values (monetary values) of environmental degradation; as a response, other indicators (geNDP and SNI) have been elaborated. Greened economy net domestic product (geNDP) estimates national income in a hypothetical future in which the economy must meet certain environmental standards and the impact is estimated by internalizing the costs of reducing environmental degradation (see, for example, de Boer *et al.*, 1994). Sustainable national income (SNI) estimates the maximum level of national income that would be obtained if the economy met all environmental standards using the current technology (see, for example, Verbruggen *et al.*, 2002). More recently, the more comprehensive environmental sustainability index (ESI) has been elaborated (see Esty *et al.*, 2005). ESI integrates 76 data sets by tracking natural resource endowments, past and present pollution levels, environmental management efforts, and the capacity of a society to improve its environmental performance into 21 indicators of environmental sustainability, combining them with equal weights for 146 countries. ESI gives scores between 0 and 100 and a higher index value represents better environmental conditions for a country.

[1] The system of national accounts (SNA) includes stocks of natural resources, pollutant and material (energy) flow accounts at the industry level, expenditures incurred by industries, government and households to protect the environment. Assets are evaluated either as net present value or net price. The environmental protection expenditure represents part of society's effort to reduce damages to environment and includes taxes or subsides and the activities of pollution-abatement by industries. For early work on environmental accounting, see, for example, Repetto et al., 1989

Although the above mentioned indicators and descriptive statistics have been provided in environmental accounts, there is no consensus over which indicators to use. Moreover, each indicator serves a somewhat different policy purpose. In that context, some of the above indices assign pre-determined fixed arbitrary weights, to "actual" pollution levels and, as such, these indices are constructed as arbitrary combinations of "actual" pollution levels. Rather than using the average contributions of the actual estimates of pollution to form a single estimate of overall pollution we obtain a range of values that is defined by the worst and best-case scenarios. In other words, our approach can be viewed as obtaining those hypothetical models where the chosen weights define the best-worst combinations of GHG components that would be obtained with the current levels of emissions as a benchmark. These extreme bounds would suggest the directions where policy makers would need to devote their efforts to obtain improvements in environmental quality by reducing emission levels.

In this paper, we focus on one theme of environmental quality, that is greenhouse gas (GHG) emissions. We construct an aggregate index of GHG emissions for the environmental quality of a country based on stochastic dominance (SD hereafter) analysis. As a benchmark we use an index that is based on the *average actual* contributions of the respective GHG emission types to the total (i.e. CO_2, methane, nitrous oxide and other greenhouse gas emissions) to obtain indices that stochastically dominate the chosen benchmark. We find "worst" and "best" case scenarios, where environmental degradation is at its maximum and minimum, respectively. Constructing an index based on SD analysis has advantages since the index will be efficient, in that it results from the least variable combination of components that offers the maximum/minimum level of environmental degradation (or environmental "risk") over time for each country, or group of countries. Thus, the "worst" and "best" indices can be used as two extreme bounds to assess environmental quality for the group of countries considered and obtain rankings for worst and best-case offenders (polluters). Relatively large data sets are available, so that the weighting scheme is data driven. The index is constructed in a way such that the weights given to each component in each sub-index will make it stochastically dominate all other competitor indices. In this context for example, the worst-case scenario will be based on a hybrid index with the highest weights for those components whose gas emissions have been increasing at a fastest rate over time. These "fast-moving" components will be identified as the ones that produce the highest environmental degradation over time.

In other words, the worst-case scenario rankings correspond to the case where degradation is at its maximum and as such efforts should be concentrated towards reducing those "fast moving" components that make it up. In the case of the best-case scenario we get the opposite picture. From a policy perspective, the worst-case scenario is the most relevant, as it identifies the gas components affecting pollution more severely over time.

More precisely, in this paper we employ two complementary SD approaches. Firstly, we construct an environmental quality index from greenhouse gas (GHG) emissions, by employing consistent stochastic dominance efficient (SDE) tests.

The methodology employed in this paper is based on multi-variate (multidimensional) comparisons of country panel data over various years. In an application to optimal portfolio construction in finance, Scaillet and Topaloglou 2010, ST hereafter, use SD efficiency tests to compare a given portfolio with an optimal diversified portfolio constructed from a set of assets. The same approach has been applied recently by Pinar *et al.* 2012 to construct a human development index (HDI) that is consistent with a best case scenario for development. Agliardi *et al.* 2012 employ SD efficiency tests to construct an optimal country risk index with differential component weights for economic, political, and financial risk indices. Differently from the above-mentioned papers, here we apply the SD approach for a worst/best case scenario analysis, so that the indices we obtain will achieve the maximum/minimum level of emission degradation for the set of countries we consider.

The worst-case scenario (i.e., obtaining the maximum level of emission degradation) will suggest the most effective way to reduce overall emissions if a common global action were undertaken by all, where each country were to take a similar action in order to reduce emissions. In that case, priority would need to be given to emission types that are the worst contributors to the overall GHG emissions rather than assigning fixed arbitrary weights, to "actual" pollution levels, as in the case of ESI. Of course one could simply use the average actual contribution of each respective GHG type to the total to form the weights of an index that could be used as a benchmark. In this case, however, this choice would only be based on the first moment (i.e., average emissions) and as such it would ignore the importance of the empirical distribution of different emission types across countries and over time. Obviously, there is a global contribution to each type of emission, however, their distribution across countries varies extensively. For the majority of countries, their highest contribution to total emissions has been CO_2 compared to other GHG types (methane, nitrous oxide and other GHG emissions over time). However, this does not apply to all countries as for example, in 2005, 33 countries emitted more methane, including the major methane emitter Brazil, than CO_2. Moreover, the distribution of each emission type across countries also varies as for example, all emission types are positively skewed, and as such higher averages are driven by some major outlier contributors. Therefore, if all countries were to decide to take a common unified action to tackle emissions, using average actual contributions as a guide would not constitute an efficient way to do so, as only the first moment would be taken into account. This is not the case for the worst and best-case bounds that we obtain using nonparametric SDE analysis as the latter relies instead on the characterization of the whole distribution. In that context, the best-case scenario would suggest the most optimistic (i.e., the least effective) method to cut GHG emissions, as it stresses the GHG types that are the least deteriorating (slowest-moving) over time.

Secondly, we employ consistent SD tests from Barrett and Donald 2003, BD hereafter, to examine the dynamic progress of each separate GHG emission (i.e., CO_2, methane, nitrous and other greenhouse gas emissions) over time from 1990 to 2005 within 5-year horizons. Hence, 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 dimensions of the different GHG emissions that are fast-moving (slow-moving), resulting in the deterioration (or improvement) of the environmental quality for all countries over the period we analyze. Furthermore, pair-wise SD tests allow us to examine the major industry contributors to the GHG emissions at any given time.[2] For that matter, at a given time, we compare each industry contribution to GHG emissions with all possible other industries to uncover the industry which contributes the most to total emissions. We shed a light on questions such as: "Given that GHG emissions not only vary over time but also across industries, is there a general increase (decrease) in GHG emissions over time? If so, which industry has been the major contributor to those increases (decreases) in GHG emissions?" To summarize, we first obtain improvements/deteriorations over time for all types of GHG emissions and then complement these findings by pair-wise industry comparisons to determine the major contributors to GHG emissions from 1990 to 2005. This approach will uncover those industries that contributed the most to emissions, but also may offer direction for potential changes in how these industries evolve over time with respect to environmental quality and consequent policy intervention.

The findings of this paper are three-fold.

First of all, our main result is the derivation of an index for environmental quality based on SDE analysis with differential component weights. This index will provide the maximum (minimum) level of environmental degradation - or maximum (minimum) environmental risk - using as a benchmark an index that is based on the *average actual* contributions of the respective GHG emission types to the total. In other words, we find the "worst" and "best" case scenarios, corresponding to an interval with the most pessimistic and optimistic weighting scheme of emissions. Then, countries are ranked according to their index of environmental quality for the worst and best case scenarios and their ranking is compared with alternative rankings (for example, the ranking of the Kyoto Protocol, Annex I, and the Environmental Sustainability Index, ESI). Overall, the rankings remain substantially stable for the high ranking countries between 1990 and 2005 using the best and worst case scenario indices. However, for both ESI and its GHG emission dimension rankings there have been some major rank reversals. The riskiest five countries in our worst case emission degradation index (i.e., worst offenders) are China, the United States, Russian Federation, India, and Japan, whereas the ESI GHG dimension ranked these countries as 32nd, 37th, 10th, 47th, and 92nd, respectively. Similarly, the riskiest five countries according to the ESI GHG dimension are the Democratic People's Republic of Korea, Turkmenistan, Trinidad and Tobago, Ukraine, and Kazakhstan, whereas these countries are ranked in our worst case scenario as 41st, 61st, 69th, 20th, and 25th respectively. Both ranking methods display significant differences even though they are significantly correlated and only the

[2] Among the GHG emissions, we have data on the contribution of each industry to CO_2, methane, nitrous emissions.

Russian Federation is ranked highly (i.e., it is a major polluter) in both rankings.

Secondly, over time SD comparisons for GHG emissions give insights of the progress of environmental quality between 1990 and 2005. We find that there has been a general increase in the CO_2 emissions in the 15-year horizon (between 1990 and 2005) at the 10% significance level, which has been driven mostly by the increase of the CO_2 emissions from the gas fuel consumption. On the other hand, there has been neither a general increase nor decrease in the methane and nitrous emissions and their sub-sectors between 1990 and 2005. However, there has been a general increase in the other GHG emissions within 5-year horizons between 1990 and 2000, which has been driven mostly by the general increase in the hydrofluorocarbon (HFC) emissions over that period. Finally, the only emission that registered a general decrease was the perfluorocarbon (PFC) emission from 1990 to 1995 and no general deterioration or improvement found for sulfur hexafluoride (SF6) over the whole period.

The third set of findings consists of detailed industry comparisons for different type of emissions. Pair-wise CO_2 emission comparisons of different sub-industries indicate that the major industry contributor to the CO_2 emissions has always been the electricity and heat production sector, while the transport sector has been the second contributor between 1990 and 2005. Furthermore, the liquid fuel consumption released more CO_2 emissions when compared with the gaseous and solid fuel consumption over the whole period. For both methane and nitrous emissions, the agricultural sector has been the major contributor followed by the energy sector from 1990 to 2005. Overall, the major industries contributing to emissions have been the same for the period between 1990 and 2005. Finally, when different types of GHG emissions are compared, we find a consistent ordering among them over time. CO_2 emissions have always been polluting the environment more than methane, nitrous and other GHG emissions between 1990 and 2005. These findings are consistent with the fact that the components that are assigned high weights in the worst case scenario using the SDE approach are the ones which are the driving (fast-moving) industries concerning the release of particular emissions such as those from CO_2 which is the main contributor to total GHG emissions. Finally, the way these industries evolve over time with respect to environmental degradation offers useful guidelines for the direction of environmental protection and public policy intervention for achieving sustained improvements in the environmental quality.

The plan of the paper is as follows. The methodology is presented in Sections 2 and 3. In particular, Section 2 presents the SD methodology to construct the overall environmental degradation index. Section 3 describes the pair-wise SD methodology from BD 2003, which is employed for over time and sub-industry comparisons. Section 4 discusses the data, the empirical results and the ranking analysis and finally Section 5 concludes.

2 The SD Efficiency methodology

In this section we present the test statistic for the SD efficiency of the environmental degradation index constructed from GHG emissions. Let us consider a strictly stationary process $\{\boldsymbol{Y}_t; t \in \mathbb{Z}\}$ with values in $\mathbb{R}^n$. The observations consist in a realization of $\{\boldsymbol{Y}_t;\ t = 1, ..., T\}$. These data correspond to observed values of the n different constituent components of the given percentage contribution of different types of emissions to the total GHG emission, or the percentage contribution of each industry to the total emissions of a given GHG type**,** τ, which is taken as a benchmark index. We denote by $F(\boldsymbol{y})$, the continuous cdf of $\boldsymbol{Y} = (Y_1, ..., Y_n)'$ at point $\boldsymbol{y} = (y_1, ..., y_n)'$.

Let us consider an alternative emission degradation index $\boldsymbol{\lambda} \in \mathbb{L}$, where $\mathbb{L} := \{\boldsymbol{\lambda} \in \mathbb{R}^n_+ : \boldsymbol{e}'\boldsymbol{\lambda} = 1\}$ with $\boldsymbol{e}$ for a vector made of ones. Throughout the paper, the SD efficiency methodology is presented and discussed according to the worst case scenario. However, reversing the empirical distributions by multiplying them with minus one or reversing the order of the two cumulative distribution functions in the maximization problem (i.e., reversing the cdf's of emission in the hypothesis testing and in the construction of the test statistics by changing the order of cdf's associated with τ and λ**,** in expression 1 or changing the minimization problem in expression 2 with the corresponding maximization problem) describes the best case scenario weighting scheme. The test statistic that maximizes the distance between any alternative and the benchmark will capture the worst case scenario, whereas when the distance is minimized (i.e., negative distance is maximized), then the environmental degradation will be at a minimum at the given emission level.

Let us denote by $G(z, \boldsymbol{\lambda}; F)$ the cdf of the composite degradation index value $\boldsymbol{\lambda}'\boldsymbol{Y}$ at point z given by $G(z, \boldsymbol{\lambda}; F) := \int_{\mathbb{R}^n} \mathbb{I}\{\boldsymbol{\lambda}'\boldsymbol{u} \leq z\} dF(\boldsymbol{u})$ where $\mathbb{I}$ denotes the indicator function $\mathbb{I}(\boldsymbol{\lambda}'\boldsymbol{u} \leq z)$ (Davidson and Duclos 2000).

Define for $z \in \mathbb{R}$:

$$\begin{aligned}
\mathcal{J}_1(z, \boldsymbol{\lambda}; F) &:= G(z, \boldsymbol{\lambda}; F), \\
\mathcal{J}_2(z, \boldsymbol{\lambda}; F) &:= \int_{-\infty}^{z} G(u, \boldsymbol{\lambda}; F) du = \int_{-\infty}^{z} \mathcal{J}_1(u, \boldsymbol{\lambda}; F) du, \\
\mathcal{J}_3(z, \boldsymbol{\lambda}; F) &:= \int_{-\infty}^{z} \int_{-\infty}^{u} G(v, \boldsymbol{\lambda}; F) dv du = \int_{-\infty}^{z} \mathcal{J}_2(u, \boldsymbol{\lambda}; F) du,
\end{aligned}$$

and so on.

Following Davidson and Duclos (2000) we obtain:

$$\mathcal{J}_j(z, \boldsymbol{\lambda}; F) = \int_{\mathbb{R}^n} \frac{1}{(j-1)!} (z - \boldsymbol{\lambda}'\boldsymbol{u})^{j-1} \mathbb{I}\{\boldsymbol{\lambda}'\boldsymbol{u} \leq z\} dF(\boldsymbol{u}).$$

The general hypotheses for testing the stochastic dominance efficiency of order j of $\boldsymbol{\tau}$, hereafter SDE_j, can be written as:

$$\begin{aligned} H_0^j :& \mathcal{J}_j(z, \boldsymbol{\tau}; F) \leq \mathcal{J}_j(z, \boldsymbol{\lambda}; F) \quad \text{for all}\, z \in \mathbb{R}\, \text{and for all}\, \boldsymbol{\lambda} \in \mathbb{L}, \\ H_1^j :& \mathcal{J}_j(z, \boldsymbol{\tau}; F) > \mathcal{J}_j(z, \boldsymbol{\lambda}; F) \quad \text{for some}\, z \in \mathbb{R}\, \text{or for some}\, \boldsymbol{\lambda} \in \mathbb{L}. \end{aligned}$$

Under the null hypothesis H_0^j there is no composite emission degradation index λ constructed from the set of components, the different type of emissions contributing to the total GHG emissions or industries that are contributing to a particular emission type, that dominates the index τ at order j. In this case, $\mathcal{J}_j(z, \tau; F)$ is always lower than $\mathcal{J}_j(z, \lambda; F)$ for all possible indices λ for any z. Under the alternative hypothesis H_1^j, a composite degradation index λ exists, such that for some z (i.e., emission level), $\mathcal{J}_j(z, \tau; F)$ is larger than $\mathcal{J}_j(z, \lambda; F)$. Thus, when $j = 1$, the index τ is stochastically inefficient at first order if and only if some other index λ dominates it at some z. Put in another way, the index τ is stochastically efficient at first order if and only if there is no index λ that dominates it at all levels of emissions (risk levels). SD can be specified at first and second order when $j = 1$ and $j = 2$, respectively.

We say that the distribution of the composite emission degradation index λ dominates the distribution of the benchmark (i.e., contribution of each industry to a particular emission type or different type of emissions' contribution to the total GHG emissions) index τ stochastically at the first-order (SD1) if, for any degradation (risk) level z, $G(z, \tau; F) \geq G(z, \lambda; F)$. If z denotes an emission level, then the previous inequality implies that the proportion of countries in the distribution λ with value of emission smaller than z is not larger than the proportion of such countries in τ. If the composite index λ dominates the index τ at first order, then there is always less emission degradation in τ than in λ. We can test whether the benchmark weights are the worst or best case scenarios, or whether we can construct a composite index $\boldsymbol{\lambda}$ from the set of the components of emissions (i.e., either industries or emission types) in the respective index that dominates the benchmark weights.

The general hypotheses for testing the SD efficiency of an emission index with benchmark weights $\boldsymbol{\tau}$ becomes:

$$\begin{aligned} H_0 :& G(z, \boldsymbol{\tau}; F) \leq G(z, \boldsymbol{\lambda}; F) \quad \text{for all}\, z \in \mathbb{R}\, \text{and for all}\, \boldsymbol{\lambda} \in \mathbb{L}, \\ H_1 :& G(z, \boldsymbol{\tau}; F) > G(z, \boldsymbol{\lambda}; F) \quad \text{for some}\, z \in \mathbb{R}\, \text{or for some}\, \boldsymbol{\lambda} \in \mathbb{L}. \end{aligned}$$

The empirical counterpart is simply obtained by integrating with respect to the empirical distribution $\hat{F}$ of F, which yields:

$$\mathcal{J}_j(z, \boldsymbol{\lambda}; \hat{F}) = \frac{1}{T} \sum_{t=1}^{T} \frac{1}{(j-1)!} (z - \boldsymbol{\lambda}' \mathbf{Y}_t)^{j-1} \mathbb{I}\{\boldsymbol{\lambda}' \mathbf{Y}_t \leq z\},$$

where $\mathbb{I}$ denotes the indicator function $\mathbb{I}(\boldsymbol{\lambda}' \mathbf{Y}_t \leq z)$ (Davidson and Duclos 2000) and can be rewritten more compactly for $j \geq 2$ as:

$$\mathcal{J}_j(z, \boldsymbol{\lambda}; \hat{F}) = \frac{1}{T} \sum_{t=1}^{T} \frac{1}{(j-1)!} (z - \boldsymbol{\lambda}' \mathbf{Y}_t)_+^{j-1}.$$

The test statistics and the asymptotic distribution of $\hat{F}$ are discussed in Scaillet and Topalaglou (2010). In particular, we follow Scaillet and Topalaglou (2010) and consider the weighted Kolmogorov-Smirnov type test statistic

$$\hat{S}_j := \sqrt{T}\frac{1}{T}\sup_{z,\boldsymbol{\lambda}}\left[\mathcal{J}_j(z,\boldsymbol{\tau};\hat{F}) - \mathcal{J}_j(z,\boldsymbol{\lambda};\hat{F})\right],$$

and a test based on the decision rule:

$$\text{“ reject} \quad H_0^j \quad \text{if} \quad \hat{S}_j > c_j\text{”},$$

where c_j is some (appropriate) critical value. In order to make the result operational, we need to find an appropriate critical value c_j. Since the distribution of the test statistic depends on the underlying distribution, we rely on a block bootstrap method to simulate p-values (see section 3 of Scaillet and Topaloglou, 2010 and Appendix D2 of Pinar *et al.*, 2012 for block bootstrap methods).

The test statistic $\hat{S}_1$ for first order stochastic dominance efficiency is derived using the following mixed integer programming formulations:

$$\max_{\mathbf{z},\boldsymbol{\lambda}} \hat{S}_1 = \sqrt{T}\frac{1}{T}\sum_{t=1}^{T}(L_t - W_t) \tag{1a}$$

$$\text{s.t.} M(L_t - 1) \leq z - \boldsymbol{\tau}'\mathbf{Y}_t \leq ML_t, \qquad \forall t \tag{1b}$$

$$M(W_t - 1) \leq z - \boldsymbol{\lambda}'\mathbf{Y}_t \leq MW_t, \qquad \forall t \tag{1c}$$

$$\boldsymbol{e}'\boldsymbol{\lambda} = 1, \tag{1d}$$

$$\boldsymbol{\lambda} \geq 0, \tag{1e}$$

$$W_t \in \{0,1\},\ L_t \in \{0,1\}, \qquad \forall t \tag{1f}$$

with M being a large constant.

The model is a mixed integer program maximizing the distance between the sum over all scenarios of two binary variables, $\frac{1}{T}\sum_{t=1}^{T} L_t$ and $\frac{1}{T}\sum_{t=1}^{T} W_t$ which represent $G(z,\boldsymbol{\tau};\hat{F})$ and $G(z,\boldsymbol{\lambda};\hat{F})$, respectively (the empirical cdf of $\boldsymbol{\tau}$ and $\boldsymbol{\lambda}$ at a given emission level z). According to inequalities (1b), L_t equals 1 for each scenario $t \in T$ for which $z \geq \boldsymbol{\tau}'\mathbf{Y}_t$, and 0 otherwise. Analogously, inequalities (1c) ensure that W_t equals 1 for each scenario for which $z \geq \boldsymbol{\lambda}'\mathbf{Y}_t$. Equation (1d) defines the sum of all emission component weights to be unity, while inequality (1e) disallows for negative weights. This formulation allows us to test the dominance of the index constructed with benchmark weights (τ) over any potential linear combination λ of the contributing factors (i.e., number of industries contributing to a particular emission or emission types contributing to total GHG emissions) that are in the respective index.

When some of the variables are binary, corresponding to mixed integer programming, the problem becomes NP-complete (non-polynomial, i.e., formally intractable). We can see that there is a set of at most T values, say $R = \{r_1, r_2, ..., r_T\}$, containing the optimal value of the variable z. A direct consequence is that we can solve the original problem by solving the smaller problems $P(r)$, $r \in R$, in which z is fixed to r. Then we take the value for z that yields the best total result. The advantage is that the values of the L_t variables are known in $P(r)$. In other words, the number of countries below a given emission level, z, is known for the index that is constructed with benchmark weights.

The reduced form of the problem is as follows:

$$
\begin{aligned}
&\min \sum_{t=1}^{T} W_t \\
&\text{s.t.} \boldsymbol{\lambda}' \mathbf{Y}_t \geq r - (r - M_t) W_t, \quad \forall t \in T \\
&\quad \boldsymbol{e}' \boldsymbol{\lambda} = 1, \\
&\quad \boldsymbol{\lambda} \geq 0, \\
&\quad W_t \in \{0, 1\}, \quad \forall t \in T.
\end{aligned} \tag{2a}
$$

A similar procedure is used in the formulation of the test statistic for stochastic dominance at the second-order (SD2 hereafter) (see appendix E2 of Pinar *et al.*, 2012, for details about testing for SD2 and its practical implementation).

3 Tests for SD pair-wise comparisons (over time and between sub-industries)

In this section we consider SD pair-wise comparisons of a given emission variable over two points in time. In particular, we examine the stochastic dominance of the different types of GHG emissions (i.e., CO_2, methane, nitrous oxide, other GHG, HFC, PFC and SF6 emissions) over a fifteen year period (from 1990 to 2005) and determine whether there has been a deterioration or improvement in each type of emission over time. In addition, SD pair-wise test are employed for the sub-industry comparisons for CO_2, methane, nitrous oxide, other GHG emissions at a given point in time. In this case we have a pair-wise comparison of a given emission type over time (or sub-industry contribution at a given point in time), such as the CO_2 emissions in year 1990 and in year 1995 (or electricity, heat production sector and transport sector contribution to CO_2 emissions in 1990). Take total GHG emissions.[3] We define $G(z, F)$ the *cdf* of the emissions at a level of z given by $G(z, F) := \int_{\mathbb{R}} \mathbb{I}\{u \leq z\} dF(u)$ where z being the emission level.

Suppose we have (possibly) dependent samples of emissions from two populations (such as a group of countries at two different points in time) that have associated cumulative distribution functions (*cdf's*) given by F_1 and F_2, and

[3] For simplicity, hereafter we discuss the pair-wise SD tests for emission comparisons over time; however, pair-wise tests will also be applied to sub-industry or different type of emission comparisons at a given time.

the functions $\mathcal{J}_j(z, F_1)$ and $\mathcal{J}_j(z, F_2)$. In this context, SD1 of F_1 over F_2 corresponds to $\mathcal{J}_1(z, F_1) \leq \mathcal{J}_1(z, F_2)$ or $G(z, F_1) \leq G(z, F_2)$ for all z, i.e., for all emission levels. When this occurs, emissions in the population, summarized by F_1, is at least as large as that in the F_2 population, for any utility function U that is an increasing monotonic function of $z - i.e.$, $U'(z) \geq 0$.

How is this related to emissions over time? Suppose we have n countries in total. If the *cdf* of emissions in 1990, $F_2(z)$, is always at least as large as that of the *cdf* in 1995, $F_1(z)$, at any emission level, then the proportion of countries below a particular emission level for the year 1990 is higher than that of 1995. Therefore, the 1995 emissions stochastically dominate its 1990 counterpart in the first-order. When the two *cdf* curves intersect, then the ranking is ambiguous. In this situation we cannot state whether one distribution first-order dominates the other. This leads to an ambiguous situation which makes it necessary to use higher-order SD analysis.

SD2 of F_1 over F_2 corresponds to $\mathcal{J}_2(z, F_1) \leq \mathcal{J}_2(z, F_2)$ for all z and the emissions in the population summarized by F_1 is at least as large as that in the F_2 population, for any utility function U that is monotonically increasing and concave, that is $U'(z) \geq 0$ and $U''(z) \leq 0$. Second-order stochastic dominance is verified, not by comparing the $cdf's$ themselves, but comparing the integrals below them. We examine the area below the $F_1(z)$ and $F_2(z)$ curves. Given lower and upper boundary levels, we determine the area beneath the curves and, if the area beneath the $F_2(z)$ distribution is larger than the one of $F_1(z)$, then in this case $F_1(z)$ stochastically dominates $F_2(z)$ in the second-order sense. Since we look at the area under the distributions, second-order dominance implies simply an overall increase in the emissions and not a point-wise dominance over all the points of the support of one distribution over another. In other words, the sum of total emissions of the countries that have an emission outcome below a given emission level is always larger in one population than in another population.

The general hypotheses for testing SD of the index over time of order j can be written compactly as:

$$H_0^j : \mathcal{J}_j(z, F_1) \leq \mathcal{J}_j(z, F_2) \text{ for all } z \in [0, \overline{z}],$$
$$H_1^j : \mathcal{J}_j(z, F_1) > \mathcal{J}_j(z, F_2) \text{ for some } z \in [0, \overline{z}].$$

Stochastic dominance of any order of F_1 over F_2 implies that F_1 is no larger than F_2 at any emission level. In this case there is an increase of the emissions over time. Thus, if the emissions in 1995 dominates the emissions in 1990 at the first-order sense, then there is an increase in the emission level of each country over time. The alternative hypothesis is the converse of the null and implies that there is at least some emission levels at which F_1 (or its integral) is strictly larger than F_2 (or its integral). In other words SD fails at some point for F_1 over F_2. In this case, there can be increase in emission levels for some countries and no increase or even decrease of emission levels for some other countries over time. Hence, there is no general increase for all countries simultaneously over time.

3.1 Test Statistics

We consider two time-dependent samples from two distributions (e.g., for emissions in 1990 and 1995). The following assumptions are required to allow for different sample sizes:

Assumption 1:

(i) $\{X_i\}_{i=1}^N$ and $\{Y_i\}_{i=1}^M$ are independent random samples from distributions with $CDF's$ F_1 and F_2 respectively;

(ii) the sampling scheme is such that as $N, M \longrightarrow \infty$, $\frac{N}{N+M} = \phi$ where $0 < \phi < 1$.

Assumption 1(i) deals with the sampling scheme and is satisfied if one has samples of emissions from different segments of a population or separate samples across time. Assumption 1(ii) implies that the ratio of the sample sizes is finite and bounded away from zero.

The empirical distributions used to construct the tests are, respectively:

$\widehat{F}_1(z) = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}(X_i \le z), \qquad \widehat{F}_2(z) = \frac{1}{M}\sum_{i=1}^{M} \mathbb{I}(Y_i \le z).$

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

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

Since ζ_j is a linear operator, then

$$\zeta_j(z;\widehat{F}_1) = \frac{1}{N}\sum_{i=1}^{N}\zeta_j(z;\mathbb{I}_{X_i}) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{(j-1)!}\mathbb{I}(X_i \le z)(z - X_i)^{j-1} \tag{3}$$

where $\mathbb{I}_{X_i}$ denotes the indicator function $\mathbb{I}(X_i \le x)$ (Davidson and Duclos, 2000).

The asymptotic properties of the tests are given in BD 2003. We consider tests based on the decision rule:

$reject\ H_0^j\ if\ \ \widehat{S}_j > c_j$

where c_j are suitably chosen critical values to be obtained by simulation methods. In order to make the result operational, we need to find an appropriate critical value c_j to satisfy $P(\overline{S}_j^{F_2} > c_j) \equiv \alpha$ or $P(\overline{S}_j^{F_1,F_2} > c_j) \equiv \alpha$ (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 BD, 2003).

4 Empirical Analysis

4.1 Data and Descriptive Statistics

The data set used in this paper consists of GHG emissions (i.e., CO_2, methane, nitrous oxide, other greenhouse gas) for several countries in various years, between 1990 and 2005.[4] The main source for our data is The World Bank, Policy and Economics Environment Department.[5] Notice that not all countries have available data for all variables (e.g., in 2005, we have data on CO_2 emissions for 198 countries whereas data for methane, nitrous oxide and other greenhouse gas emissions are only available for 135 countries). As such, only countries for which there is data availability for all variables will be ranked in the overall emission degradation (risk) index. A detailed description of all the emission types and the industries contributing to them is in Appendix A. In Section 4.2 we present five sub-indices for the worst and best case emission degradation indices for the sub-emission categories together with the overall composite index of emission degradation, and in section 4.3 we list the rankings for different countries with respect to their worst and best case scenarios. In Section 4.4 we present over time SD comparisons of the different types of emission dimensions and further we compare different sub-industries to uncover the major contributors to GHG emissions. The results for pair-wise SD comparisons are given in Tables B.1 to B.8 of Appendix B for space limitations.[6]

4.2 SD efficient emission degradation index

In this section we start by first testing the efficiency of the overall GHG emission degradation index. The variables used for emission degradation index are: CO_2, methane (CO_2 equivalent), nitrous oxide (CO_2 equivalent), other greenhouse gas emissions (CO_2 equivalent), for a unbalanced data set of 135 countries for four time periods, that is, 1990 (consisting of 110 countries), 1995 (consisting of 134 countries), 2000 (consisting of 135 countries), and 2005 (consisting of 135 countries). The average contribution of CO_2, methane, nitrous oxide, and other greenhouse gas emissions to the total GHG emissions is 70.28%, 20.05%, 8.2%, and 1.47% respectively and these average contributions are taken as the weights that make up the benchmark.

We proceed to construct many other hybrid composite emission degradation indices, λ, consisting of the four components of emissions listed above (CO_2, methane, nitrous oxide, other greenhouse gas emissions) that stochastically dominate the benchmark emission degradation (risk) outcome τ, in the first-order sense (e.g. for which $G(z,\tau;F) > G(z,\lambda;F)$). There are 315 and 514 different such composite degradation indices λ's for the worst- and best-case scenarios respectively. Table I(a) summarizes the results for the worst-case scenario, presenting the average weights of the 315 hybrid composites that dominate the benchmark emission degradation (risk) levels (i.e., average contribution of each emission category to the total GHG emissions). On the other hand, Table I(b)

[4] Co2 emissions consist of annual data from 1960 to 2008, whereas methane, nitrous and other GHG emissions consist of data in 1990, 1995, 2000 and 2005.

[5] The authors are indebted to Glenn-Marie Lange and her staff members at The World Bank for their help in providing most data.

[6] The information presented in Tables B.1 to B.8 is summarized in the text. Tables B.1 to B.8 can be removed to conserve space and can become available from the authors.

summarizes the results for the best-case scenario. The inefficiency of the benchmark weights given to each emission type indicates that they are suboptimal. Our findings show that CO_2 is the main contributor to the worst-case emission degradation with a 92.76% contribution followed by methane, nitrous oxide and other greenhouse gas emissions with 5.74%, 1.26% and 0.24% weights, respectively (see Table I(a)). On the other hand, other GHG emissions contribute to the best-case scenario with a weight of 97.68%, followed by nitrous oxide emissions with a weight of 2.32% (see Table I(b)). In the most pessimistic case, CO_2 emissions contribute more than their average, whereas for the most optimistic scenario this is the case for the other GHG emissions. In other words, if there is a global action to be taken such as the Kyoto protocol to reduce emission levels and average contribution of each emission is considered as a benchmark to allocate resources accordingly, this would have resulted in a suboptimal action. Our results suggets that since the worst-case contribution is mainly due to CO_2 (i.e., more than its average contribution), more budget or resources should be allocated to reduce CO_2 emissions.

We then proceed to present our findings of the test for the first-order stochastic dominance efficiency for a number of different sub-category emission factors, such as sub-industry contributions to CO_2, methane, and nitrous oxide emissions taken separately. We then compute the weighting scheme of each respective sub-category emission factor to create sub-indices, which produce the least and the most risky (i.e., best-case and worst-case scenarios respectively) emission levels for the sample of countries under consideration.

Note that for any of the sub-categories of emissions that we analyze, one can obtain the total GHG emissions by adding each sub-components' contribution. For example, one can also obtain the average contribution of emissions for CO_2, methane, nitrous and the other GHG emissions to obtain the degradation levels over time. However, average contributions would only capture information in the first moment, something that would be adequate if the data were characterized solely by the first moment. That would be the case if other features of the distribution were not important. This is not true for the data that characterize the sub-components of GHG emissions, as clearly not each country contributes equally to the degradation levels of environmental factors (for example, the average of total GHG emissions in 2005 was 283332 kt, whereas the median was 63386 kt suggesting that emissions are positively skewed). Rather than concentrating only on an average contribution, the nonparametric SDE analysis that we employ relies instead on the characterization of the whole distribution and hence the results that we obtain are more robust.

First, we analyze the sub-industry contributions to the CO_2 emissions (i.e., CO_2 emissions from electricity and heat production, EH hereafter; CO_2 emissions from manufacturing industries and construction, MC hereafter; CO_2 emissions from other sectors, excluding residential buildings and commercial and public services, OT hereafter; CO_2 emissions from residential buildings and commercial and public services, RC hereafter; and CO_2 emissions from transport sector, TR hereafter). We take the average contribution of each sector to the total CO_2 emissions as the benchmark, i.e., 44.62%, 20.70%, 2.70%, 11.52%, and 20.46% for EH, MC, OT, RC and TR respectively. We then proceed to construct many hybrid combination of each sector, λ, consisting of the five components of sectors that stochastically dominate the benchmark emission degradation (risk) outcome τ, in the first-order sense (e.g. for which $G(z, \tau; F) > G(z, \lambda; F)$). Furthermore, we also find the best-case scenario weighting scheme by reversing the order of the two cumulative distribution functions. Tables II(a) and II(b) summarize the results, presenting the average weights of the hybrid composites that dominate the benchmark CO_2 emission degradation (risk) levels. Our findings suggest that EH sector is the main contributor to the worst-case CO_2 emission degradation with a 93.03% contribution followed by TR, OT, RC, and MC sectors with 4.58%, 0.81%, 0.80% and 0.78% weights respectively (see Table II(a)). On the other hand, OT sector is the main contributor to the best-case CO_2 emission degradation with a 98.32% contribution followed by RC with a 1.68% weight (see Table II(b)).

Similarly, we analyzed the efficiency of the sub-fuel consumption contribution to the CO_2 emissions (i.e., CO_2 emissions from gaseous, liquid and solid consumption). The average contribution of each consumption type to the total CO_2 emissions is taken as the benchmark, i.e., 18.82%, 40.03%, and 41,15% for gaseous, liquid and solid fuel consumption respectively. We find that there are many hybrid combinations of each consumption type, λ, consisting of the three components that stochastically dominate the benchmark emission degradation (risk) outcome τ, in the first-order sense. Tables III(a) and III(b) summarize the results for the worst- and best-case emission degradation index, presenting the average weights of the hybrid composites that dominate the benchmark CO_2 emission degradation levels. Therefore, the benchmark case is neither the best- nor the worst-case scenario. We find that the CO_2 emissions from liquid fuel consumption is the main contributor to the worst-case scenario with a weight of 93.52%, whereas the CO_2 emissions from gaseous fuel consumption is the main contributor to the best-case scenario with a weight of 95.58% (see Table III(a) and Table III(b) for each respective cases).

We further analyze the sub-industry contributions to the methane emissions (i.e., agriculture and energy sector) and to the nitrous oxide emissions (i.e., agriculture, industrial and energy sector) respectively. We take the average contribution of each sector to the total methane and nitrous emissions as the benchmarks (i.e., average contribution of agriculture and energy sectors to the total methane emissions are 55.87% and 44.13% respectively; and average contribution of agriculture, industrial and energy sectors to the total nitrous emissions are 79.44%, 9.14%, and 11.42% respectively). Tables IV(a) and IV(b) summarize the worst- and best-case weighting scheme of the sectors contributing to the methane emissions respectively. The average contribution of agriculture and energy sectors found to be neither the worst- nor the best-case scenario. We find that the agriculture sector is the major contributor to the worst-case methane emissions with a weight of 82.03% and if the energy sector weighted relatively more than its average contribution, with a weight of 96.87%, one would make the most optimistic view of emission degradation for methane (see Table IV(a) and IV(b) respectively for details). The industries contributing to the nitrous oxide emissions, we also find that the average contribution of each sectors is neither the worst- nor the best-case scenarios. Table V(a) summarizes the worst-case scenario in which we find that the agriculture sector is the main contributor to the worst-case scenario nitrous oxide emission degradation with a weight of 98.02%. We also conducted the best-case scenario for the nitrous oxide emissions and Table V(b) presents the results. We find that in the best-case scenario of the nitrous oxide emissions, industrial and energy sectors get more weight than their average contribution to the total nitrous oxide emissions, with weights of 63.53% and 35.20% respectively.

Even though, other GHG emissions do contribute relatively less when compared to the CO_2, methane, nitrous oxide emissions, each emission categorized under the category of other GHG emissions (i.e., HFC, PFC and SF6 emissions). We analyze whether the average contributions of HFC, PFC and SF6 with weights 50.28%, 21.03%, and 28.69% respectively to the total other GHG emissions that form the benchmark are being worst- or best-case scenario. Tables VI(a) and VI(b) summarize the results for the worst- and best-case scenarios respectively. We find that the HFC is the main contributor to the worst-case scenario with a weight of 87.08% (see Table VI(a)), and the PFC is the main contributor to the best-case scenario with a weight of 82.18%.

4.3 Ranking analysis and comparisons with alternative emission indices

In this section, we present the rankings of countries for the actual, worst- and best-case scenarios for total GHG emissions and compare these degradation levels with other existing degradation indices.

Table VII presents the rankings of the various countries in terms of the actual, worst- and best-case environmental degradation for years 1990, 1995, 2000 and 2005 for the top 30 countries that are the highest polluters according to the actual total GHG emissions. Our findings suggest that the countries with higher actual values are also ranked in higher positions both in the worst- and best-case emission degradation levels from 1990 to 2005. For example, in 2005, China, the United States, the Russian Federation, India and Japan not only were the highest actual emitters, but also in the worst-case scenario. The only country among the five that moved out of the first five positions to a better ranking in the best-case scenario is India due to its relatively low levels of other GHG emissions. A similar trend has been observed for 1990, 1995 and 2000. Countries which ranked in the first five positions with actual emissions have always ranked in higher positions in the worst-case scenario since the main contributing factor for these countries has been CO_2 emissions. A similar trend over time further documents the need to design effective policies to reduce CO_2 emissions primarily in order to reduce total GHG emissions.

Since the rankings in the worst- and the best-case scenarios vary for each country, we provide the ranking difference between the worst- and the best-case scenarios for each country for the years 1990, 1995, 2000 and 2005. If the rank difference is a negative value, that means that the country ranks in a lower position in the best-case scenario. This would mean that more is to be gained if these counties were to reduce their emissions as they contribute more to the overall total emission reductions. On the other hand, if the change is positive, that would mean that a country ranks in a higher position in the best-case scenario when compared to the worst-case scenario. This would imply that these countries would contribute less to the overall emission reduction, if they would follow policies based on the best-case scenario weights. Table VIII summarizes the highest possible relative rank reversals for 30 countries for 1990, 1995, 2000 and 2005. In 2005, Qatar, Trinidad and Tobago, Syria, Iraq, Lebanon would have moved to a relatively lower ranking by 80, 61, 54, 53, and 48 positions if the best-case scenario is taken when compared to the worst-case one (for example, Qatar is ranked in the 54th position in the worst-case scenario, whereas it is ranked in the 134th position in the best-case scenario). In other words, these countries have been emitting relatively more CO_2 and methane emissions compared to their other GHG emissions and nitrous oxide emissions. Furthermore, rank reversals highlight those countries that could have contributed relatively more to reducing total GHG by switching from the least effective hypothetical allocation (i.e., best-case scenario) to the most effective one (i.e., worst case scenario). On the other hand, the Democratic Republic of the Congo, Zambia, Cameroon, Mozambique, Tajikistan would have moved to a relatively higher ranking in the best-case scenario when compared to their rankings in the worst-case scenario. In this case, these rank reversals, represent the countries that could have contributed relatively least by switching from the least effective hypothetical allocation (i.e., best-case scenario) to the most effective one (i.e., worst case scenario).

We further provide the dynamic progress of each country's relative ranking from 1990 to 2005 when we consider their rankings in the worst- and best-case scenario. In other words, we list countries which have showed a remarkable deterioration or improvement in their rankings within the 15-year period in each case. We have 110 overlapping countries for 1990 and 2005, therefore we only consider these countries to analyze changes in country's ranking over time. Tables IX(a) and IX(b) present the top ten countries which experienced the largest downward and upward movements in their ranking between 1990 and 2005 for the worst- and best-case respectively.[7] All the counties which had the largest downward movement in the rankings of worst-case scenario experienced a decrease in their CO_2 emissions which highlights the countries that have been taking most efficient reduction in the emission levels. For example, Romania and Bulgaria experienced a decrease of 63901kt and 74304kt in their CO_2 emissions, respectively, whereas the Democratic Republic of Congo experienced a decrease in its methane emissions by 40147kt. Similarly, countries which had an upward movement in their rankings experienced an increase their CO_2 emissions. For example, Vietnam's CO_2 emissions increased by 386% when compared to the 1990 levels. On the other hand, in the best-case scenario, the

[7] If 10th largest upward and/or upward movement in the ranking position is shared by more than one countries, we also reported them.

largest downward movements are mainly driven with the decrease in other GHG emissions, whereas the largest upward movements are driven by an increase in each country's other GHG emissions ranging from 115kt (i.e., Malta) to 2021kt (i.e., Singapore).

Furthermore, observe that our ranking differs from that of the commitments of countries in the Kyoto Protocol. It is well known that the Kyoto Protocol establishes assigned amounts of emissions for various countries (see Annex I and Annex B[8]), with the intention of reducing their average emissions during 2008-2012 to about 5 percent below 1990 levels. Under the Kyoto Protocol, only the Annex I countries have committed themselves to national or joint reduction targets that range from a joint reduction of 8% for the European Union (originally the 15 states that were EU members in 1997, when the Kyoto Protocol was adopted), of 7% for the United States, 6% for Japan, Canada, Hungary and Poland, 5% for Croatia, and 0% for New Zealand, Russia and Ukraine; moreover, a +1% was allowed to Norway, +8% for Australia and +10% for Iceland. The rankings we obtain in Table VII remained substantially stable for the high ranking countries over the four periods. Notice that the following countries have the highest values for the overall worst-case and best-case environmental quality: China, the United States, the Russian Federation, India, Japan, Brazil, Germany, Canada.[9] Countries which committed themselves to a reduction, such as the United States, Japan and Canada or no increase such as Russian Federation constantly stayed in the higher rankings. Among these, the United States, Japan and Canada experienced a constant increase in their CO_2 emissions which kept them in the higher rankings for actual emissions and the worst-case scenario. China and India which were not part of the Kyoto protocol, also experienced a remarkable increase in all types of emissions which kept them in the higher rankings in all cases.

We also conducted ranking comparisons of our worst- and best-case emission degradation index with the ESI rankings in 2005 (see Esty *et al.*, 2005). Since our index represents the riskiest and the least risky emission degradation levels (the worst- and the best-case environmental degradation), we converted the ESI measure by multiplying its score with a negative one to represent ESI rankings from the riskiest to the least risky country in order to facilitate a direct comparison between the two rankings.[10] Furthermore, a sub-dimension of ESI, that is, ESI greenhouse gas emissions, is closely linked to our worst- and best-case emission degradation index, which is then compared with our indices.[11] Table X presents the rankings of the overlapping 125 countries in four rankings. The rankings differ significantly, especially when it comes to the environmentally riskiest countries (i.e., countries that degrade the environment the most). Even

[8] See http://unfccc.int/kyoto_protocol/items/2830.php

[9] Note that Germany and Russing Federation were not included in the 1990 rankings.

[10] Even though the best-case scenario is the least risky emission levels for group of countries, yet the higher values in the best-case scenario represent a riskier environment. Therefore to compare ESI values with the worst- and best-case scenarios, ESI values converted that the higher values present riskier environment.

[11] The greenhouse gas emissions dimension of ESI consists of indicators: carbon emissions per million US dollars GDP and carbon emissions per capita.

though, ESI covers 21 indicators, yet they do not capture total contributions to the environmental degradation but are normalized with per capita or percentage values. Similarly, the GHG dimension of ESI and the worst- and base-scenario rankings differ significantly for two reasons. The GHG dimension of ESI only accounts for carbon emissions which are in turn measured in terms of per million US dollars GDP and per capita. In the worst- and best-case emission degradation index, we also account for methane, nitrous oxide and other GHG emissions and we measure each emission in total values. Furthermore, we conduct a Spearman rank correlation analysis between the four rankings and Table XI presents the Spearman rank correlation coefficients and their significance levels. We find that ESI and ESI GHG dimension is positively and significantly correlated and the worst- and the best-case indices are positively and significantly correlated as expected. However, the ESI ranking is not significantly correlated with neither the worst- nor the best-case scenario rankings. On the other hand, the ESI GHG dimension ranking is positively and significantly correlated with the worst-case scenario rankings at the 1% significance level but not with the best-case scenario ranking.

Even though there exist a significant and positive correlation between the worst-case emission degradation index and the ESI GHG dimension, there exist some major relative rank reversals. The riskiest five countries in our worst-case emission degradation index (i.e., worst offenders) are China, the United States, the Russian Federation, India, and Japan, whereas ESI GHG dimension ranked these countries as 32nd, 37th, 10th, 47th, and 92nd, respectively. Similarly, the riskiest five countries according to ESI GHG dimension are the Democratic People's Republic of Korea, Turkmenistan, Trinidad and Tobago, Ukraine, and Kazakhstan, whereas these countries are ranked in the worst-case scenario as 41st, 61st, 69th, 20th, and 25th. Both rankings obviously display a remarkable rank reversal even though they are significantly correlated and only the Russian Federation is ranked highly in both rankings.

4.4 Pair-wise SD comparisons

In the next subsection we present over time pair-wise SD comparisons of emissions. We provide the evolution over time (i.e., either deterioration or improvement) of CO_2, methane, nitrous oxide, HFC, PFC, and SF6 emissions and their sub-industry contributions between 1990 and 2005 within 5-year periods. Furthermore, we conduct SD pair-wise sub-industry comparisons of GHG emissions to analyze which industry has been major contributor to the particular emission between 1990 and 2005.[12] We therefore find the major industries which contributed most to different emission types for the years 1990, 1995, 2000 and 2005. The results are presented in Tables B.1 to B.8 of Appendix B.

[12] We test whether the following year dominates the previous one (i.e., deterioration over time) and reversely also test whether the previous year dominates the following year (i.e., improvement over time). If there is no conclusive dominance among comparisons, we reported them as NA representing no dominance.

4.4.1 CO_2 emissions

First, we present the findings from the pair-wise SD comparisons of CO_2 emissions from 1990 to 2005. The different panels of Table B.1 and B.2 present the results for SD1 and SD2 over the period under investigation based on bootstrap methods from BD (2003) for stochastic dominance with dependent data for total, sub-industry and sub-fuel CO_2 emissions. We first test whether the total CO_2 emissions in 1995 dominate the CO_2 emissions in 1990, and separately we test whether CO_2 emissions from each individual sector (e.g., CO_2 emissions from the electricity and heat production in 1995 dominate the CO_2 emissions from the same sector in 1990). Furthermore, we also test whether CO_2 emissions from each sub-fuel consumption (e.g., emissions from gaseous fuel consumption in 1995 dominate its counterpart in 1990). These consecutive tests will allow us to analyze whether over time deteriorations (or improvements) have occurred in total CO_2 emissions and, in addition, which sector and/or sub-fuel consumption is mainly responsible for such deteriorations (or improvements).

The vertical columns of Tables B.1 and B.2 represent the years from 1995 to 2005 that are tested for stochastic dominance against years from 1990 to 2000. Percentage levels in the tables represent the significance level of stochastic dominance (e.g., in Table B.1(a): CO_2 emissions in 2005 stochastically dominates the CO_2 emissions in 1990 in the first- and second-order sense at the 10 percent level). NA represents that there is no dominance at that order.

The results from Table B.1(a) suggest that there has been no general increase in total CO_2 emissions within a 10 year-period. In all such cases SD1 is rejected. However the findings in Table B.1(a) suggest that there has been a general increase in the total CO_2 emissions from 1990 to 2005, since there is a dominance at first-order at the 10% significant level. Therefore, there has been a clear general degradation in CO_2 emissions within 15 years. The results for each subsector given from Table B.1(b) to Table B.1(f), where it can be seen that there has been no dominance in each sub-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. Finally, from Table B.2(a) to Table B.2(c), we have the results from CO_2 emissions from different sub-fuel consumption. We find that there has been a general increase in the CO_2 emission from gaseous fuel consumption within a 15-year period (from 1990 to 2005), since there is a dominance at first-order at the 5% significance level. Overall, there has been a significant increase in the total CO_2 emission from 1990 to 2005 which were mostly driven by the CO_2 emissions from the gaseous fuel consumption between the same period. In other words, general degradation of CO_2 was mainly due to the general degradation in CO_2 emissions from the gaseous fuel consumption.

After analyzing the progress of the CO_2 emissions over time, we present the findings from the pair-wise SD comparisons by looking at CO_2 emissions from different sub-industries (i.e., emissions from electricity and heat production; manufacturing industries and construction; other sectors, excluding residential buildings and commercial and public services; residential buildings and commercial and public services; and the transport sector) in 1990, 1995, 2000 and 2005. We further compare the CO_2 emissions from different types of fuel consumption (i.e., gaseous, solid and liquid fuel consumption) in the years 1990, 1995, 2000 and 2005. The panels in Tables B.3 and B.4 present the results for sub-industry and sub-fuel comparisons respectively.

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 sense. In other words, CO_2 emissions from electricity and heat sectors has been always higher than CO_2 emissions from any other industry. 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 sense. The contribution of other sectors to the CO_2 emissions are the 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.[13] Overall, there has been a clear robust ranking of sectors (from the highest CO_2 emitting sector to the lowest one) over the period of 1990-2005. These findings complement the previous SDE findings that the CO_2 emissions from electricity and heat sectors and the CO_2 emissions from other sectors, excluding residential buildings and commercial and public services are the major contributors to the worst- and best-case scenarios respectively (see two panels of Table II).

Finally, panels in Table B.4 present the results of the comparisons between CO_2 emissions from different type of fuel consumption from 1990 to 2005. The results suggest that over the whole period, the liquid fuel consumption has always been the major contributor to the CO_2 emissions since CO_2 emissions from this type dominate the emissions from the gaseous and solid fuel consumption at a first-order sense at the 1% significance level. This finding is consistent with the SDE findings that the liquid fuel consumption is the major contributor to the worst-case scenario to the CO_2 emissions (see the first panel of Table III). On the other hand, CO_2 emission from the solid fuel consumption dominate the emission from the gaseous fuel consumption at the second-order sense at 10% significance level in 1990 and 2005 (i.e., sum of the total CO_2 emissions from the solid fuel consumption have been higher than the sum of the CO_2 emissions from the gaseous fuel consumption but there has been no point-wise increase for all countries) but the relationship between these two types of fuel consumption is ambiguous in 1995 and 2000.

4.4.2 Methane emissions

In this section, we present the findings from the pair-wise SD applications for the methane emissions from 1990 to 2005. We investigate the evolution of

[13] The significance level of the dominance of each sector on the other one has been different at different periods. We have not gone into a detailed explanation since those results are self-explanatory and we concentrate only on discussing the general patterns.

total methane emissions, methane emissions from the 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 period.[14]

We also conduct the pair-wise comparisons of methane emissions from the agriculture and energy sectors in 1990, 1995, 2000 and 2005. For the whole period, methane emissions from the agriculture sector have always been higher than methane emission from the energy sector. The panels of Table B.5 present the findings for the years 1990 to 2005 with 5-year increments. Methane emissions from the agriculture sector dominates the methane emissions from the energy sector at the first-order sense at 1% significance level. In other words, for any given methane emission level, there has been always more countries emitting above that level in 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, something that complements the SDE findings that the agricultural sector is the major contributor to the worst-case scenario (see the first panel of Table IV).

4.4.3 Nitrous oxide emissions

In this section, we present the pair-wise SD applications for the nitrous oxide emissions from 1990 to 2005. We analyze the progress of total nitrous oxide emissions, nitrous oxide emissions from the agriculture, the industrial and the energy sectors respectively between 1990 and 2005. 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.

Similar to the CO_2 and methane emissions, we also 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 have always been higher than the other two sectors, while nitrous oxide emissions from the energy sector have always been higher than the nitrous oxide emissions from the industrial sector for the whole period. The panels of Table B.6 present the findings for the years 1990 to 2005 with 5-year increments. Nitrous oxide emissions from the agriculture sector dominate the nitrous oxide emissions from the energy and industrial sectors at the first-order sense at 1% significance level and similarly nitrous oxide emissions from the energy sector dominate those of the industrial sector in the first-order sense at a significance level of 1% over the whole period. In other words, for any given nitrous oxide emission level, there has been always more countries emitting above that level in agriculture sector than the energy and industrial sector.

[14] Given the space limitation, we have not offered the findings in tables when there exist no significant stochastic dominance for the whole section. However, the results are available upon request from the authors.

Overall, there has been a clear robust ranking of sectors (from the highest nitrous oxide emitting sector to the lowest one) over the period 1990-2005.

4.4.4 Other GHG emissions

Even though the other GHG emissions have always been contributing less to the total, when compared to CO_2, methane or nitrous oxide emissions, we apply the same procedure to the former as we did with the latter cases. We conduct pair-wise SD comparisons for the other GHG emissions and its sub-components from 1990 to 2005. The four panels of Table B.7 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. There has been a general increase in the total GHG emissions in 5-year horizons between 1990 and 2000, yet no clear indication between 2000 and 2005. 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 in the first-order sense at the 1% significance level. There has been 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 in the first-order sense at the 5% and 1% significance levels respectively.[15] In other words, for any given PFC emission level, there has been always less countries emitting above that level in 1990 when compared with 1995 and 2005.

4.4.5 Comparison between GHG emissions

Finally, we present the pair-wise SD comparisons between CO_2, methane, nitrous oxide and other GHG emissions in 1990, 1995, 2000 and 2005. The four panels of the Table B.8 give the results for comparisons between each type of emissions for each respective year. The 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. In other words, for any given CO_2 equivalent emission level, there has 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 oxide and other GHG emissions between 1990 and 2005 in the first order-sense at the 1% significance level making it the second major GHG emissions contributor. Similarly, for any given CO_2 equivalent emission level, there has been always 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.

[15] 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 decrease over time in PFC emissions, the testing horizon is reversed.

These findings are consistent with the fact that the components that are assigned higher weights in the worst-case scenario in the the SDE approach (CO_2 emissions and, subsequently, methane emissions) are the ones which are the driving (fast-moving) variables in the sub-index of GHG emissions constructed in Section 4.2 (see the first panel of Table I).

Overall, our results help policy makers to identify policies for achieving improvements in environmental quality. In other words, policies aiming to reduce CO_2 emissions needs to be given priority when compared with the other types of emissions. In order to achieve lower levels of CO_2 emissions, special attention has to be given to those industrial sectors which are mainly responsible for these emissions, namely electricity and heat production and the transport sector. In that case, there are alternative options available to policy makers to reduce emissions. For example, Palmer and Burtraw (2005) discuss for the United States such policies as the renewables portfolio standard (RPS) for a given state that states that a minimum percentage of the electricity produced or sold in the state must come from renewable sources. Their analysis suggests that the RPS policy seems to be the best method for promoting renewable sources of energy and appears to be reasonably effective at achieving direct reductions in carbon emissions (for a recent renewable energy policy recommendations for the United States and the European Union, see Schmalensee, 2012). Furthermore, as the second major industry that contributes to CO_2 emissions is the transport sector, a tax on gasoline will eventually decrease carbon emissions. To that effect, in a recent application, Davis and Kilian (2011) find that a ten-cent per gallon increase in the gasoline tax would reduce vehicle carbon emissions in the United States by about 1.5% and therefore reduce overall carbon emissions by approximately 0.5%. Finally, Yan and Crookes (2009) analyze the transport sector's impact on emissions in China and project the future impact of different alternative policies, such as private vehicle control, fuel economy regulation and, fuel tax and bio-fuel promotion. They find that such policies would have decreased emissions by 40% when compared to the case where no actions were taken.

5 Conclusion

In this paper, we derive worst- and best-case scenarios of emission degradation indices based on SD efficiency analysis with differential component weights. The worst- and best-case scenarios suggest that if a global action (i.e., allocation of resources) were to be taken to reduce GHG emissions by all countries, giving more importance to some emission types than their average actual contributions to the total, that would result in a best- or and worst-case improvement depending on the use of pessimistic or optimistic weights respectively. In this respect, allocating more resources to reduce emissions from the energy and the heat production sectors that contribute to CO_2 emissions and the agriculture sector that contributes to the methane and nitrous oxide emissions considerably more than their actual average contribution to each respective emission category would tend to result in an improvement for environmental quality. Similarly, if one were to allocate more resources to reduce CO_2 emissions considerably more than its average share would tend to result in an improvement, when compared using the average shares as a benchmark for environmental quality.

We also proceed to rank countries according to their worst- and best-case scenarios when the total GHG emissions are considered and their rankings are compared with those of the Kyoto Protocol and ESI and its GHG dimension. The rankings remained substantially stable for the high ranking countries between 1990 and 2005 for the worst- and best-case scenarios. Moreover, we find that countries which committed themselves to a reduction in Kyoto Protocol, such as the United States, Japan and Canada consistently stayed in the higher rankings, since they all experienced a constant increase in their CO_2 emissions. When the worst- and best-case scenario rankings are compared with ESI and its GHG emission dimension rankings, we find major relative rank reversals**.** These rank reversals highlight those countries that could have contributed relatively most (least) to the reduction of total GHG by switching from the least effiective hypothetical allocation (i.e., best-case scenario) to the most effective (i.e., worst case scenario).

Furthermore, we employ consistent pair-wise SD tests to examine the dynamic progress of GHG emissions (i.e., CO_2, methane, nitrous oxide and other GHG, HFC, PFC, and SF6 emissions). We find that there has been a general increase in CO_2 emissions in a 15-year horizon at the 10% significance level (between 1990 and 2005). Also, there has been a general increase in total GHG emissions within 5-year horizons between 1990 and 2000 which has been driven mostly by the general increase in HFC emissions over the same period. The only emissions for which there has been a general decrease are the PFC emissions from 1990 to 1995. Finally, we find a consistent ordering among greenhouse emissions over time. CO_2 emissions have always been polluting the environment more than methane, nitrous and other GHG emissions above any emission level between 1990 and 2005. We also conduct pair-wise SD tests which allow us to analyze the major industry contributors to the emissions. We find that the major industry contributing to CO_2 emissions has always been the electricity and heat production sectors followed by the transport sector between 1990 and 2005. For both methane and nitrous emissions, the agricultural sector has always been the major contributor, followed by the energy sector from 1990 to 2005. As such, there has been a clear ordering of industries which were the main responsible for environmental degradation over time.

Our results shed light on the direction for potential changes in how these industries evolve over time with respect to environmental quality and can help identify policies for achieving improvements and provide consequent guidelines for policy intervention. Environmental protection and the timing of policy intervention have become a priority and indeed a challenge for many governments.

Finally, for possible future work one could apply this methodology to obtain the worst-case (best-case) indices of other components of the environmental quality for a country, or group of countries. One could find the weighting scheme of each sub-index (i.e. of GHG emissions, of water pollution, of other determinants of the environmental quality), and then construct an overall index of environmental quality, which corresponds to the overall worst/best case scenarios for all countries. Such composite index could be used to construct a comprehensive measure of wealth, which corresponds to the overall worst/best case scenarios, and complements the literature on genuine saving and sustainable development. As Hamilton and Clemens (1999) state, "thinking about sustainable development and its measurement leads naturally to a conception of the process of development as one of portfolio management". This implies that one has to consider not only assets and liabilities in the national balance sheet (i.e., natural resources, produced assets, human capital and pollution stocks), but also their appropriate weights. Our approach provides this portfolio analysis and the weighting scheme consistent with the worst/best (pessimistic/optimistic) scenarios.

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Table I(a). The worst case scenario stochastic efficient weighting for sub-emission contribution to the total GHG emissions					
Number of observations	Number of dominating weighting schemes	Carbon dioxide emissions	Methane emissions	Nitrous oxide emissions	Other greenhouse gas emissions
N	**n**	***Average of dominating weighting schemes***			
514	315	0.9276	0.0574	0.0126	0.0024

Table I(b). The best case scenario stochastic efficient weighting for sub-emission contribution to the total GHG emissions					
Number of observations	Number of dominating weighting schemes	Carbon dioxide emissions	Methane emissions	Nitrous oxide emissions	Other greenhouse gas emissions
N	**n**	***Average of dominating weighting schemes***			
514	514	0.000	0.000	0.0232	0.9768

Table II(a). The worst case scenario stochastic efficient weighting for sub-industry contribution to Co2 emissions						
Number of observations	Number of dominating weighting schemes	EH	MC	OT	RC	TR
N	**n**	***Average of dominating weighting schemes***				
537	367	0.9303	0.0078	0.0081	0.0080	0.0458
Note: EH represents the emissions from "electricity and heat production"; MC represents the emissions from "manufacturing industries and construction"; OT represents the emissions from "other sectors, excluding residential buildings and commercial and public services"; RC represents the emissions from "residential buildings and commercial and public services"; TR represents the emissions from "transport sector".						

Table II(b). The best case scenario stochastic efficient weighting for sub-industry contribution to Co2 emissions						
Number of observations	Number of dominating weighting schemes	EH	MC	OT	RC	TR
N	**n**	***Average of dominating weighting schemes***				
537	537	0.0000	0.0000	0.9832	0.0168	0.0000
Note: EH represents the emissions from "electricity and heat production"; MC represents the emissions from "manufacturing industries and construction"; OT represents the emissions from "other sectors, excluding residential buildings and commercial and public services"; RC represents the emissions from "residential buildings and commercial and public services"; TR represents the emissions from "transport sector".						

Table III(a). The worst case stochastic efficient weighting for sub-fuel consumption contribution to Co2 emissions				
Number of observations	Number of dominating weighting schemes	Gaseous-fuel consumption	Liquid-fuel consumption	Solid-fuel consumption
N	**n**	***Average of dominating weighting schemes***		
750	730	0.0136	0.9352	0.0511

Table III(b). The best case stochastic efficient weighting for sub-fuel consumption contribution to Co2 emissions				
Number of observations	Number of dominating weighting schemes	Gaseous-fuel consumption	Liquid-fuel consumption	Solid-fuel consumption
N	**n**	***Average of dominating weighting schemes***		
750	137	0.9558	0.0107	0.0335

Table IV(a). The worst case scenario stochastic efficient weighting for sub-industry contribution to methane emissions			
Number of observations	Number of dominating weighting schemes	Agriculture sector	Energy sector
N	**n**	***Average of dominating weighting schemes***	
540	503	0.8203	0.1797

Table IV(b). The best case scenario stochastic efficient weighting for sub-industry contribution to methane emissions			
Number of observations	Number of dominating weighting schemes	Agriculture sector	Energy sector
N	**n**	***Average of dominating weighting schemes***	
540	526	0.0313	0.9687

Table V(a). The worst case scenario stochastic efficient weighting for sub-industry contribution to nitrous oxide emissions				
Number of observations	Number of dominating weighting schemes	Agriculture sector	Industry sector	Energy sector
N	**n**	***Average of dominating weighting schemes***		
540	516	0.9802	0.0189	0.0009

Table V(b). The best case scenario stochastic efficient weighting for sub-industry contribution to nitrous oxide emissions				
Number of observations	Number of dominating weighting schemes	Agriculture sector	Industry sector	Energy sector
N	**n**	***Average of dominating weighting schemes***		
540	539	0.0127	0.6353	0.3520

Table VI(a). The worst case scenario stochastic efficient weighting for sub-category emission contribution to other GHG emissions				
Number of observations	Number of dominating weighting schemes	HFC	PFC	SF6
N	**n**	***Average of dominating weighting schemes***		
540	339	0.8708	0.0595	0.0697
Note: HFC represents the hydrofluorocarbon emissions; PFC represents the perfluorocarbon emissions; SF6 represents the sulfur hexafluoride emissions.				

Table VI(b). The best case scenario stochastic efficient weighting for sub-category emission contribution to other GHG emissions				
Number of observations	Number of dominating weighting schemes	HFC	PFC	SF6
N	**n**	***Average of dominating weighting schemes***		
540	408	0.0126	0.8218	0.1656
Note: HFC represents the hydrofluorocarbon emissions; PFC represents the perfluorocarbon emissions; SF6 represents the sulfur hexafluoride emissions.				

Table VII. The actual, worst and best case scenario ranking of countries in 1990, 1995, 2000 and 2005							
	Ranking in 2005				Ranking in 2000		
Country Name	Actual case	Worst case	Best case	Country Name	Actual case	Worst case	Best case
China	1	1	2	United States	1	1	1
United States	2	2	1	China	2	2	2
Russian Federation	3	3	3	Russian Federation	3	3	3
India	4	4	10	India	4	4	7
Japan	5	5	4	Japan	5	5	4
Brazil	6	15	7	Germany	6	6	5
Germany	7	6	5	Brazil	7	14	9
Canada	8	7	6	Canada	8	8	6
Indonesia	9	19	20	United Kingdom	9	7	12
United Kingdom	10	8	11	Mexico	10	11	17
Mexico	11	12	16	Australia	11	16	15
Iran, Islamic Rep.	12	10	22	Italy	12	9	10
Australia	13	16	14	Indonesia	13	21	19
Italy	14	9	9	France	14	13	8
France	15	14	8	Korea, Rep.	15	10	11
Korea, Rep.	16	11	12	Iran, Islamic Rep.	16	15	22
South Africa	17	13	24	South Africa	17	12	24
Ukraine	18	20	43	Ukraine	18	17	42
Spain	19	18	13	Poland	19	18	26
Saudi Arabia	20	17	29	Spain	20	20	14
Poland	21	21	23	Saudi Arabia	21	19	34
Thailand	22	22	37	Turkey	22	22	18
Turkey	23	23	15	Thailand	23	23	45
Argentina	24	28	35	Argentina	24	26	31
Pakistan	25	30	39	Pakistan	25	34	44
Nigeria	26	33	46	Venezuela, RB	26	25	23
Malaysia	27	24	40	Nigeria	27	38	52
Egypt, Arab Rep.	28	26	21	Netherlands	28	24	13
Kazakhstan	29	25	56	Egypt, Arab Rep.	29	27	20
Venezuela, RB	30	29	26	Malaysia	30	29	50

Note: The actual ranking represents the ranking according to the total GHG emissions. The worst and best case represents the ranking of countries when each emission is weighted with the worst and best case scenario weighting scheme of each emissions from Table I(a) and Table I(b) respectively.

Table VII continued…							
	Rankings in 1995				Rankings in 1990		
Country Name	Actual case	Worst case	Best case	Country Name	Actual case	Worst case	Best case
United States	1	1	1	United States	1	1	1
China	2	2	3	China	2	2	3
Russian Federation	3	3	5	India	3	4	5
India	4	5	8	Japan	4	3	2
Japan	5	4	2	United Kingdom	5	5	11
Germany	6	6	4	Brazil	6	15	6
Brazil	7	17	7	Canada	7	6	4
United Kingdom	8	7	10	France	8	8	7
Canada	9	8	6	Poland	9	9	31
Ukraine	10	9	37	Italy	10	7	14
France	11	11	9	Australia	11	12	13
Italy	12	10	14	Mexico	12	11	15
Indonesia	13	20	18	Indonesia	13	19	16
Mexico	14	15	17	South Africa	14	10	27
Australia	15	16	16	Iran, Islamic Rep.	15	14	20
Poland	16	14	29	Korea, Rep.	16	13	12
South Africa	17	13	27	Spain	17	16	9
Korea, Rep.	18	12	11	Argentina	18	23	19
Iran, Islamic Rep.	19	18	20	Saudi Arabia	19	17	21
Spain	20	19	12	Turkey	20	21	18
Thailand	21	22	30	Romania	21	20	24
Saudi Arabia	22	21	32	Netherlands	22	18	10
Argentina	23	29	31	Thailand	23	25	28
Turkey	24	23	19	Venezuela, RB	24	22	17
Kazakhstan	25	25	56	Congo, Dem. Rep.	25	65	26
Netherlands	26	24	13	Nigeria	26	37	46
Venezuela, RB	27	26	21	Pakistan	27	29	30
Pakistan	28	35	43	Belgium	28	24	48
Nigeria	29	55	54	Colombia	29	33	49
Malaysia	30	30	34	Myanmar	30	69	39
Note: The actual ranking represents the ranking according to the total GHG emissions. The worst and best case represents the ranking of countries when each emission is weighted with the worst and best case scenario weighting scheme of each emissions from Table I(a) and Table I(b) respectively.							

Table VIII. The major improvements and deteriorations in the rankings in 1990, 1995, 2000 and 2005							
Improvements/Deteriorations in 2005				Improvements/Deteriorations in 2000			
Country Name	Δ	**Country Name**	Δ	**Country Name**	Δ	**Country Name**	Δ
Qatar	-80	Congo, Dem. Rep.	63	Qatar	-69	Tajikistan	77
Trinidad & Tobago	-61	Zambia	57	Trinidad & Tobago	-61	Congo, Dem. Rep.	68
Syrian Arab Republic	-54	Cameroon	54	Oman	-56	Zambia	64
Iraq	-53	Mozambique	54	Syrian Arab Rep.	-54	Cameroon	59
Lebanon	-48	Tajikistan	52	Lebanon	-49	Sudan	54
Tunisia	-46	Latvia	49	Estonia	-44	Mozambique	50
Dominican Republic	-43	Norway	47	Turkmenistan	-42	Tanzania	46
Chile	-39	Armenia	43	Dominican Rep.	-42	Norway	45
Hong Kong SAR	-35	Serbia	41	Jordan	-42	Slovak Rep.	43
Yemen, Rep.	-35	Ethiopia	40	Kazakhstan	-41	Ethiopia	39
Estonia	-35	Sudan	39	Chile	-40	Angola	38
Morocco	-34	Iceland	38	Uzbekistan	-39	Iceland	36
Sri Lanka	-34	Tanzania	35	Tunisia	-37	Serbia	34
Vietnam	-32	Switzerland	33	Iraq	-36	Myanmar	33
Kazakhstan	-31	Paraguay	32	Jamaica	-33	Luxembourg	32
Algeria	-29	Singapore	29	Azerbaijan	-31	Congo, Rep.	30
Croatia	-27	Brunei	29	Libya	-29	Guatemala	29
Turkmenistan	-26	Lithuania	28	Hong Kong SAR	-29	Paraguay	27
Libya	-26	Angola	26	Yemen, Rep.	-28	Ghana	27
Azerbaijan	-25	New Zealand	26	Algeria	-27	Switzerland	26
Jamaica	-24	Guatemala	26	Morocco	-27	Namibia	25
Ukraine	-23	Sweden	24	Sri Lanka	-26	Benin	25
Jordan	-23	Myanmar	23	Ukraine	-25	New Zealand	24
Uzbekistan	-21	Malta	23	Czech Republic	-25	Sweden	24
Philippines	-19	Uruguay	22	Thailand	-22	Singapore	23
Colombia	-19	Congo, Rep.	21	Bulgaria	-22	Latvia	23
Oman	-18	Denmark	20	Panama	-22	Ireland	20
Ecuador	-18	Ireland	18	Malaysia	-21	Senegal	18
Honduras	-18	Israel	17	Philippines	-21	Nepal	17
Panama	-18	Cambodia	17	Macedonia, FYR	-21	Israel	16
Note: Δ represents the difference between the ranking of a country in the worst case scenario and the ranking in the best case scenario. If Δ is a negative value, then the country ranks in a lower position in the best case scenario when compared to the worst case. On the other hand, if Δ is a positive value, then the country ranks in a higher position in the best case scenario when compared to the worst case.							

Table VIII continued...							
Improvements/Deteriorations in 1995				Improvements/Deteriorations in 1990			
Country Name	**Δ**	**Country Name**	**Δ**	**Country Name**	**Δ**	**Country Name**	**Δ**
Qatar	-68	Tajikistan	99	Trinidad & Tobago	-47	Cameroon	65
Trinidad and Tobago	-60	Congo, Dem. Rep.	68	Qatar	-44	Iceland	64
Oman	-50	Zambia	66	Bulgaria	-38	Ghana	44
Lebanon	-46	Cameroon	61	Oman	-38	Norway	43
Turkmenistan	-45	Ethiopia	58	Syrian Arab Rep.	-32	Zambia	43
Jordan	-44	Mozambique	57	Jordan	-32	Bahrain	41
Czech Rep.	-43	Sudan	56	Luxembourg	-31	Mozambique	40
Estonia	-43	Myanmar	49	Tunisia	-30	Congo, Dem. Rep.	39
Algeria	-42	Tanzania	49	Lebanon	-30	Tanzania	39
Uzbekistan	-42	Norway	46	Algeria	-27	Angola	37
Azerbaijan	-41	Ghana	42	Chile	-25	Ethiopia	35
Bulgaria	-39	Angola	40	Jamaica	-25	Sudan	32
Syrian Arab Rep.	-39	Paraguay	34	Belgium	-24	Myanmar	30
Jamaica	-35	Iceland	34	Ecuador	-24	Congo, Rep.	26
Kazakhstan	-31	Cambodia	33	Iraq	-23	Benin	26
Iraq	-31	Benin	33	Poland	-22	Cambodia	25
Libya	-30	New Zealand	32	Portugal	-22	Paraguay	24
Slovak Republic	-30	Congo, Rep.	32	Finland	-21	Botswana	24
Dominican Rep.	-30	Bosnia & Herzegovina	30	Dominican Rep.	-21	Namibia	23
Tunisia	-29	Botswana	26	Gabon	-21	New Zealand	22
Ukraine	-28	Nepal	25	Morocco	-20	Bolivia	21
Belarus	-28	Bolivia	22	Cyprus	-20	Nepal	20
Luxembourg	-28	Kenya	22	Kuwait	-19	Togo	19
Moldova	-27	Uruguay	22	Albania	-19	Israel	15
Macedonia, FYR	-27	Namibia	21	Brunei	-19	Uruguay	13
Chile	-24	Togo	21	Cuba	-18	Switzerland	11
Morocco	-24	Switzerland	20	Yemen, Rep.	-18	Kenya	11
Lithuania	-23	Cote d'Ivoire	20	South Africa	-17	Cote d'Ivoire	11
Brunei	-23	Nicaragua	20	Peru	-17	Nicaragua	11
Ecuador	-21	Slovenia	17	Colombia	-16	Brazil	9

Note: Δ represents the difference between the ranking of a country in the worst case scenario and the ranking in the best case scenario. If Δ is a negative value, then the country ranks in a lower position in the best case scenario when compared to the worst case. On the other hand, if Δ is a positive value, then the country ranks in a higher position in the best case scenario when compared to the worst case.

Table IX(a). Largest downward and upward movement in the worst case ranking between 1990 and 2005			
Country Name	Largest downward movement	Country Name	Largest upward movement
Congo, Dem. Rep.	23	Vietnam	-25
Bulgaria	22	Qatar	-18
Gabon	22	Honduras	-14
Albania	20	Sri Lanka	-14
Romania	14	Malaysia	-13
Zimbabwe	14	Cambodia	-12
Zambia	13	Guatemala	-11
Cuba	13	Angola	-11
Mongolia	12	United Arab Emirates	-9
Hungary	12	Nigeria	-9
Brunei	12		
Table IX(b). Largest downward and upward movement in the best case ranking between 1990 and 2005			
Country Name	Largest downward movement	Country Name	Largest upward movement
Bahrain	42	Guatemala	-35
Iceland	39	Cyprus	-35
Ghana	35	Brunei Darussalam	-33
Hong Kong SAR	27	Oman	-32
Botswana	21	Ireland	-27
Romania	19	Singapore	-27
Cameroon	18	Malta	-25
Iraq	17	Belgium	-22
Mongolia	16	Portugal	-19
Benin	16	Denmark	-18
Note: The largest downward and upward movements in the rankings are obtained for the actual, worst and best case by subtracting each country’s ranking in 1995 from its respective ranking in 2005 for each case.			

Table X. Country rankings according to the ESI, ESI GHG dimensions, worst case scenario, and the best case scenario				
Country Name	**ESI ranking**	**ESI GHG dimension ranking**	**Worst-case scenario ranking**	**Best-case scenario ranking**
Korea, Dem. Rep.	1	1	41	25
Turkmenistan	2	2	61	85
Iraq	3	29	39	88
Uzbekistan	4	7	34	54
Haiti	5	119	121	120
Sudan	6	118	82	46
Trinidad and Tobago	7	3	69	125
Kuwait	8	12	43	50
Yemen, Rep.	9	80	77	108
Ethiopia	10	120	93	57
Saudi Arabia	11	11	17	28
China	12	32	1	2
Tajikistan	13	43	120	75
Iran, Islamic Rep.	14	18	10	22
Pakistan	15	71	30	38
Lebanon	16	41	80	124
Zimbabwe	17	50	88	91
Libya	18	22	53	78
Philippines	19	86	42	60
Vietnam	20	61	36	67
Angola	21	94	75	51
Korea, Rep.	22	46	11	12
Dominican Republic	23	44	78	117
El Salvador	24	96	102	99
Syrian Arab Republic	25	16	46	96
Egypt, Arab Rep.	26	42	26	21
Guatemala	27	102	85	62
Bangladesh	28	115	59	70
Congo, Dem. Rep.	29	122	101	43
Belgium	30	69	37	29
Togo	31	91	125	119
United Arab Emirates	32	23	32	47
Jamaica	33	30	90	112
Ukraine	34	4	20	42
Morocco	35	79	60	92
Mozambique	36	123	119	71
Poland	37	19	21	23
India	38	47	4	10
Kenya	39	103	91	80
Azerbaijan	40	6	66	90
Nigeria	41	98	33	45
Algeria	42	36	35	63
Mexico	43	45	12	16
Romania	44	21	40	48
South Africa	45	24	13	24
Czech Republic	46	14	31	40
Turkey	47	51	23	15
Macedonia, FYR	48	25	89	94
Cote d'Ivoire	49	95	94	86

Table X continued…				
Country Name	**ESI ranking**	**ESI GHG dimension ranking**	**Worst-case scenario ranking**	**Best-case scenario ranking**
Serbia	50	20	57	18
Honduras	51	85	95	111
Benin	52	114	118	110
Nepal	53	116	113	100
Jordan	54	34	76	97
Oman	55	31	67	84
Venezuela, RB	56	26	29	26
Kyrgyz Republic	57	52	105	114
Sri Lanka	58	106	87	118
Kazakhstan	59	5	25	55
Indonesia	60	67	19	20
Spain	61	73	18	13
Thailand	62	49	22	36
Bulgaria	63	13	55	73
Mongolia	64	8	92	106
Cambodia	65	125	107	93
Greece	66	48	38	33
Italy	67	75	9	9
Nicaragua	68	72	115	107
United Kingdom	69	66	8	11
Tanzania	70	117	98	68
Israel	71	53	50	32
Bosnia and Herzegovina	72	17	71	64
Senegal	73	104	103	101
Zambia	74	121	116	65
Moldova	75	27	106	122
Georgia	76	57	108	115
Tunisia	77	76	74	116
Hungary	78	38	51	35
Cuba	79	60	72	79
Ecuador	80	59	70	87
Cameroon	81	109	109	61
Belarus	82	15	49	56
Ghana	83	111	96	95
Myanmar	84	124	79	58
Slovak Republic	85	28	64	74
United States	86	37	2	1
Armenia	87	56	114	77
Chile	88	64	47	83
Netherlands	89	78	27	19
Congo, Rep.	90	100	124	104
Malaysia	91	35	24	39
Portugal	92	70	45	52
France	93	97	14	8
Botswana	94	84	111	109
Russian Federation	95	10	3	3
Namibia	96	107	117	103
Germany	97	77	6	5
Japan	98	92	5	4
Slovenia	99	55	83	72

Table X continued…				
Country Name	**ESI ranking**	**ESI GHG dimension ranking**	**Worst-case scenario ranking**	**Best-case scenario ranking**
Panama	100	81	104	121
Denmark	101	87	56	37
Estonia	102	9	81	113
Albania	103	88	112	105
Colombia	104	93	48	66
Lithuania	105	40	84	59
Ireland	106	63	58	41
Bolivia	107	62	86	76
Croatia	108	54	73	98
Costa Rica	109	108	99	102
Paraguay	110	113	110	82
Latvia	111	58	97	53
Peru	112	101	65	69
Australia	113	33	16	14
New Zealand	114	65	68	44
Gabon	115	74	122	123
Brazil	116	99	15	7
Argentina	117	82	28	34
Austria	118	90	44	27
Switzerland	119	110	63	31
Canada	120	39	7	6
Iceland	121	89	123	89
Sweden	122	105	54	30
Uruguay	123	112	100	81
Norway	124	83	62	17
Finland	125	68	52	49

Table XI. Spearman rank correlation between ESI, ESI GHG, the worst- and the best-case scenario emission degradation indices

	ESI	ESI GHG dimension	Worst-case scenario	Best-case scenario
ESI	1			
ESI GHG dimension	0.2710*	1		
Worst-case scenario	0.0970	0.4558*	1	
Best-case scenario	-0.0849	0.1469	0.8051*	1

Note: 125 countries that have overlapping data for all indices are used to obtain the spearman rank correlations. *, **, and *** denotes the significance of the spearman rank correlation at 1%, 5% and 10% level respectively.

Appendix A

In this appendix we present the data used (i.e., type of emissions, industries and sub-fuel consumption that contributes to the emissions) for the stochastic dominance analysis.

Greenhouse gas (GHG) emissions

Variables used: Co2, Methane (Co2 equivalent), Nitrous oxide (Co2 equivalent), other greenhouse gas emissions (Co2 equivalent)

Industries:

a) Industries contributing to Co2 emissions:

i) Electricity and heat production
ii) Manufacturing industries and construction
iii) Other sectors, excluding residential buildings and commercial and public services
iv) Residential buildings and commercial and public services
v) Transport sector

b) Industries contributing to methane emissions

i) Agriculture sector
ii) Energy sector

c) Industries contributing to nitrous emissions

i) Agriculture sector
ii) Energy sector
iii) Industrial sector

Type of fuel consumption contributing to the Co2 emissions:

i) Solid consumption
ii) Liquid consumption
iii) Gas consumption

Data Set:

Co2 emissions consist of unbalanced data set (annual data between 1960 and 2008) and having Co2 emission values for 198 countries in 2008

Methane, nitrous oxide and other greenhouse emissions (all measured in Co2 equivalent) have data in 1990, 1995, 2000, and 2005 (balanced data for 135 countries)

Other greenhouse gas emissions consist of hydrofluorocarbons (HFC), perfluorocarbons (PFC), and sulfur hexafluoride (SF6).

Appendix B

In this appendix we present the over time pair-wise stochastic dominance of CO_2, methane, nitrous oxide, HFC, PFC, and SF6 emissions and their sub-industry contributions between 1990 and 2005 within 5-year periods. Furthermore, SD pair-wise comparisons of different sectors contributing to GHG emissions are provided for the years 1990, 1995, 2000 and 2005.

Table B.1. Pair-wise SD comparisons of total and sub-industry Co2 emissions over time										
a) Total Co2 emissions						b) CO2 emissions from electricity and heat production				
		1990	1995	2000				1990	1995	2000
1995	SD1	NA	-	-		1995	SD1	NA	-	-
	SD2	NA	-	-			SD2	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
2005	SD1	10%	NA	NA		2005	SD1	NA	NA	NA
	SD2	10%	NA	NA			SD2	NA	NA	NA
c) CO2 emissions from manufacturing industries and construction						d) CO2 emissions from other sectors, excluding residential buildings and commercial and public services				
		1990	1995	2000				1990	1995	2000
1995	SD1	NA	-	-		1995	SD1	NA	-	-
	SD2	NA	-	-			SD2	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
2005	SD1	NA	NA	NA		2005	SD1	NA	NA	NA
	SD2	NA	NA	NA			SD2	NA	NA	NA
e) CO2 emissions from residential buildings and commercial and public services						f) CO2 emissions from transport				
		1990	1995	2000				1990	1995	2000
1995	SD1	NA	-	-		1995	SD1	NA	-	-
	SD2	NA	-	-			SD2	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
2005	SD1	NA	NA	NA		2005	SD1	NA	NA	NA

Table B.2. Pair-wise SD comparisons of sub-fuel Co2 emissions over time										
a) CO2 emissions from gaseous fuel consumption						b) CO2 emissions from liquid fuel consumption				
		1990	1995	2000				1990	1995	2000
1995	SD1	NA	-	-		1995	SD1	NA	-	-
	SD2	NA	-	-			SD2	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
2005	SD1	5%	NA	NA		2005	SD1	NA	NA	NA
	SD2	5%	NA	NA			SD2	NA	NA	NA
iii) CO2 emissions from solid fuel consumption										
		1990	1995	2000						
1995	SD1	NA	-	-						
	SD2	NA	-	-						
2000	SD1	NA	NA	-						
	SD2	NA	NA	-						
2005	SD1	NA	NA	NA						
	SD2	NA	NA	NA						

Table B.3. Pair-wise SD comparisons of Co2 emissions from industries			
a) Sub-industry comparisons in 1990			
Industry comparisons	Dominance Outcome	SD1	SD2
EH versus MC	EH dominates MC	5%	5%
EH versus OT	EH dominates OT	1%	1%
EH versus RC	EH dominates RC	1%	1%
EH versus TR	EH dominates TR	5%	5%
MC versus OT	MC dominates OT	1%	1%
MC versus RC	MC dominates RC	1%	1%
MC versus TR	TR dominates MC	10%	10%
OT versus RC	RC dominates OT	1%	1%
OT versus TR	TR dominates OT	1%	1%
RC versus TR	TR dominates RC	1%	1%
b) Sub-industry comparisons in 1995			
Industry comparisons	Dominance Outcome	SD1	SD2
EH versus MC	EH dominates MC	5%	5%
EH versus OT	EH dominates OT	1%	1%
EH versus RC	EH dominates RC	1%	1%
EH versus TR	EH dominates TR	5%	5%
MC versus OT	MC dominates OT	1%	1%
MC versus RC	MC dominates RC	1%	1%
MC versus TR	TR dominates MC	5%	5%
OT versus RC	RC dominates OT	1%	1%
OT versus TR	TR dominates OT	1%	1%
RC versus TR	TR dominates RC	1%	1%

Note: EH represents the emissions from “electricity and heat production”; MC represents the emissions from “manufacturing industries and construction”; OT represents the emissions from “other sectors, excluding residential buildings and commercial and public services”; RC represents the emissions from “residential buildings and commercial and public services”; TR represents the emissions from “transport sector”.

Table B.3 continued...			
c) Sub-industry comparisons in 2000			
Industry comparisons	Dominance Outcome	SD1	SD2
EH versus MC	EH dominates MC	5%	5%
EH versus OT	EH dominates OT	1%	1%
EH versus RC	EH dominates RC	1%	1%
EH versus TR	EH dominates TR	10%	10%
MC versus OT	MC dominates OT	1%	1%
MC versus RC	MC dominates RC	1%	1%
MC versus TR	TR dominates MC	5%	5%
OT versus RC	RC dominates OT	1%	1%
OT versus TR	TR dominates OT	1%	1%
RC versus TR	TR dominates RC	1%	1%
d) Sub-industry comparisons in 2005			
Industry comparisons	Dominance Outcome	SD1	SD2
EH versus MC	EH dominates MC	1%	1%
EH versus OT	EH dominates OT	1%	1%
EH versus RC	EH dominates RC	1%	1%
EH versus TR	EH dominates TR	5%	5%
MC versus OT	MC dominates OT	1%	1%
MC versus RC	MC dominates RC	1%	1%
MC versus TR	TR dominates MC	5%	5%
OT versus RC	RC dominates OT	1%	1%
OT versus TR	TR dominates OT	1%	1%
RC versus TR	TR dominates RC	1%	1%

Note: EH represents the emissions from “electricity and heat production”; MC represents the emissions from “manufacturing industries and construction”; OT represents the emissions from “other sectors, excluding residential buildings and commercial and public services”; RC represents the emissions from “residential buildings and commercial and public services”; TR represents the emissions from “transport sector”.

Table B.4. Pair-wise SD comparisons of Co2 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	NA	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	NA	NA	NA
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	NA	NA	NA
LIQUID versus SOLID	LIQUID dominates	1%	1%
iv) Sub-fuel comparisons in 2005			
Industry comparisons	Dominance Outcome	SD1	SD2
GAS versus LIQUID	LIQUID dominates	1%	1%
GAS versus SOLID	SOLID dominates	NA	10%
LIQUID versus SOLID	LIQUID dominates	1%	1%
Note: GAS represents the emissions from " gaseous fuel consumption"; LIQUID represents the emissions from "liquid fuel consumption"; SOLID represents the emissions from " solid fuel consumption".			

Table B.5. Pair-wise SD comparisons of methane emissions from sectors			
a) Sub-sector comparisons in 1990			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
b) Sub-sector comparisons in 1995			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
c) Sub-sector comparisons in 2000			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
d) Sub-sector comparisons in 2005			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
Note: AGRI represents the methane emissions from "agricultural sector"; ENER represents the methane emissions from "energy sector".			

Table B.6. Pair-wise SD comparisons of nitrous oxide emissions from sectors			
a) Sub-sector comparisons in 1990			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
AGRI versus INDUS	AGRI dominates	1%	1%
ENER versus INDUS	ENER dominates	1%	1%
b) Sub-sector comparisons in 1995			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
AGRI versus INDUS	AGRI dominates	1%	1%
ENER versus INDUS	ENER dominates	1%	1%
c) Sub-sector comparisons in 2000			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
AGRI versus INDUS	AGRI dominates	1%	1%
ENER versus INDUS	ENER dominates	1%	1%
d) Sub-sector comparisons in 2005			
Industry comparisons	Dominance Outcome	SD1	SD2
AGRI versus ENER	AGRI dominates	1%	1%
AGRI versus INDUS	AGRI dominates	1%	1%
ENER versus INDUS	ENER dominates	1%	1%
Note: AGRI represents the nitrous oxide emissions from "agricultural sector"; ENER represents the nitrous oxide emissions from "energy sector"; INDUS represents the nitrous oxide emissions from "industrial sector".			

Table B.7. Pair-wise SD comparisons total 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%	NA		2005	SD1	1%	1%	1%
	SD2	1%	1%	NA			SD2	1%	1%	1%
c) PFC emissions						d) SF6 emissions				
		1995	2000	2005				1990	1995	2000
1990	SD1	5%	NA	1%		1995	SD1	NA	-	-
	SD2	5%	NA	1%			SD2	NA	-	-
1995	SD1	-	NA	NA		2000	SD1	NA	NA	-
	SD2	-	NA	NA			SD2	NA	NA	-
2000	SD1	-	-	NA		2005	SD1	NA	NA	NA
	SD2	-	-	NA			SD2	NA	NA	NA

Table B.8. Pair-wise Co2, methane, nitrous and other GHG comparisons			
a) Emission (Co2, methane, nitrous oxide and other GHG) comparisons in 1990			
Comparisons	Dominance Outcome	SD1	SD2
Co2 versus MET	Co2 dominates	5%	5%
Co2 versus NIT	Co2 dominates	1%	1%
Co2 versus OTH	Co2 dominates	1%	1%
MET versus NIT	Methane dominates	1%	1%
MET versus OTH	Methane dominates	1%	1%
NIT versus OTH	Nitrous oxide dominates	1%	1%
b) Emission (Co2, methane, nitrous oxide and other GHG) comparisons in 1995			
Comparisons	Dominance Outcome	SD1	SD2
Co2 versus MET	Co2 dominates	1%	1%
Co2 versus NIT	Co2 dominates	1%	1%
Co2 versus OTH	Co2 dominates	1%	1%
MET versus NIT	Methane dominates	1%	1%
MET versus OTH	Methane dominates	1%	1%
NIT versus OTH	Nitrous oxide dominates	1%	1%
c) Emission (Co2, methane, nitrous oxide and other GHG) comparisons in 1995			
Comparisons	Dominance Outcome	SD1	SD2
Co2 versus MET	Co2 dominates	1%	1%
Co2 versus NIT	Co2 dominates	1%	1%
Co2 versus OTH	Co2 dominates	1%	1%
MET versus NIT	Methane dominates	1%	1%
MET versus OTH	Methane dominates	1%	1%
NIT versus OTH	Nitrous oxide dominates	1%	1%
d) Emission (Co2, methane, nitrous oxide and other GHG) comparisons in 1995			
Comparisons	Dominance Outcome	SD1	SD2
Co2 versus MET	Co2 dominates	1%	1%
Co2 versus NIT	Co2 dominates	1%	1%
Co2 versus OTH	Co2 dominates	1%	1%
MET versus NIT	Methane dominates	1%	1%
MET versus OTH	Methane dominates	1%	1%
NIT versus OTH	Nitrous oxide dominates	1%	1%
Note: Co2 represents the total Co2 emissions; MET represents the total methane emissions; NIT represents the total nitrous oxide emissions; OTH represents the total other GHG emissions. All emissions are measured in same units as thousand metric tons of CO2 equivalent emissions.			

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