A new index of environmental quality

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Abstract

A weighting scheme is proposed to construct a new index of environmental quality for different countries using an approach that relies on consistent tests for stochastic dominance (SD) efficiency. The test statistics and the estimators are computed using mixed integer programming methods. The variables that are considered include countries' greenhouse gas (GHG) emissions, water pollution and forest benefits, as from the dataset of the World Bank. In the overall index of environmental quality land without forest contributes the most (with a weight around 71%), GHG emissions contribute with around 25% and water pollution contributes less (with around 4%). Moreover, countries are ranked according to their index of environmental quality and their rankings are compared with those of the Kyoto Protocol and alternative environmental indices. Then, employing a complementary SD approach, pairwise SD tests are employed to examine the dynamic progress of each separate variable over time, from 1990 to 2010, within 5-year horizons. Furthermore, pairwise SD tests are used to examine the major industry contributors to the GHG emissions and water pollution at any given time, to uncover the industry which contributes the most to total emissions and water pollution. It turns out that the components that are assigned high (low) weights in the SD approach are the ones that are the driving/fast-moving (holding back/slow-moving) variables in the sub-indices of GHG emissions and water pollution.

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1 Introduction

Traditionally, wealth stock estimates have focused on produced capital, intangible capital (human capital, social capital) health and the quality of institutions. Recently, the concept of genuine saving has been introduced (Hamilton, 1994; Hamilton and Clemens, 1999; Arrow, Dasgupta and Mäler, 2003; Arrow, Dasgupta et al, 2004; Arrow, Dasgupta et al. 2010; Agliardi, 2011), which provides a broader indicator of sustainability, by evaluating changes in natural resources and environmental quality, in addition to the traditional measure of changes in produced assets, included in net saving, and human capital. In a recent work the World Bank (2010) has updated their previous empirical analysis (World Bank, 1997, 2006) in per capita terms in 120 countries for the year up to 2005, building on Hamilton and Clemens (1999), to estimate comprehensive investment, adding to net national saving the net additions to fossil fuels and minerals, forest cover, carbon in the atmosphere and public expenditures in education. It has been argued that growth in some countries is not sustainable because of depletion in stocks of natural resources and deterioration in the quality of environmental services (e.g. Millennium Ecosystems Assessment, 2005). And all this is exacerbated by high population growth rates.

Our paper complements the literature on genuine saving, since we aim at constructing a comprehensive measure of the main sub-components of wealth. In this paper we focus on one sub-component only, that is the environmental quality of a country. In particular, an optimal weighting scheme is proposed to construct a new index of environmental quality for different countries, using an approach that relies on consistent tests for stochastic dominance efficiency. Then, this index could be considered as a sub-index and added to other existing indices, for example, such as the Human Development Index (HDI) and a natural resource index, to find with the same methodology the optimal composite index representing a most appropriate measure of wealth for a country. Our framework yields an empirically implementable measure that can be applied also to cross-country comparisons.

There are already some indicators and descriptive statistics in environmental accounts (see United Nations, 2003). 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[1]. 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.

Several macroeconomic indicators measuring some aspects of the environmental quality of a country have been elaborated. 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

[1] For early work on environmental accounting, see Repetto et al, 1989; UN 1993.

(NAMEA) single indicators are obtained for different themes (e.g. acidification of the atmosphere, eutrofication of waters etc) by aggregating the emissions, using some common measurement unit and then comparing them with a national target level. The NAMEA, however, does not provide a single-valued indicator that aggregates across all themes. A single-valued indicator of total material requirements (TMR) can be derived from 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, the 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 (for a hypothetical model, see De Boer et al, 1994; the Swedish National Institute of Economic Research, 2000). 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, Verbrugger et al, 2000).

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. A further shortcoming is that the separate analysis of single indicators, or the composite measures listed above, ignore the dependence among the various components. Finally, the above-mentioned indicators are often based on arbitrary weighting of the relevant variables. Thus, a construction of an appropriate index of environmental quality is still to be found. In this paper we construct an aggregate index for the environmental quality of a country based on stochastic dominance (SD hereafter) analysis. 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 level of environmental risk over time for each country or group of countries. 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.

More precisely, in this paper we employ two complementary SD approaches. First, we construct an environmental index from greenhouse gas (GHG) emissions, water pollution and forest cover, 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) 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, Stengos and Topaloglou (2012) to construct a HDI that is consistent with a best case scenario for development. Agliardi et al. (2012) use the same methodology to construct an optimal country risk index with differential component weights for economic, political, and financial risk indices. In a similar manner, in this paper the index we obtain will achieve the maximum level of environmental risk for the set of countries we consider.

Secondly, we employ consistent SD tests from Barrett and Donald (2003), BD hereafter, to examine the dynamic progress of each separate GHG emissions (i.e., CO_2, methane, nitrous and other greenhouse gas emissions) and water pollution over time from 1990 to 2005 and forest cover over time from 1990 to 2010 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 environmental quality dimensions that are fast-moving (slow-moving), resulting in the deterioration (or improvement) of the environmental quality for all countries over the period we analyze. Futhermore, pair-wise SD tests allow us to examine the major industry contributors to the GHG emissions and water pollution at any given time[2]. In order words, at a given time, we compare each industry contribution to GHG emissions and water pollution with all possible other industries to uncover the industry which contributes the most to total emissions and water pollution. We shed a light on questions such as: "Given that GHG emissions or water pollution not only vary over time but also across industries, is there a general increase (decrease) in GHG emissions or water pollution over time? If so, which industry has been the major contributor to those increases (decreases) in GHG emissions or water pollution?".

To summarize, we first obtain improvements/deteriorations over time for all types of GHG emissions, water pollution and forest cover and then complement these findings by pair-wise industry comparisons to determine the major contributors to GHG emissions and water pollution from 1990 to 2005. This approach will uncover those industries that contributed the most to emissions and water pollution, 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 optimal index for the environmental quality of a country based on SD analysis with differential component weights. This index will provide the maximum level of environmental risk in a country for a given probability level and also be the least volatile over time among its set of competitors. Then, countries are ranked according to their index of environmental quality and a comparison with alternative rankings (e.g., the ranking of the Kyoto Protocol, Annex I, and the Environmental Sustainability Index, ESI) can be performed. When GHG emissions, water pollution and forest cover is considered for the overall environmental quality index, we find that land without forest contributes the most with a weight around 71%, while the contributions of emissions and water pollution are about 25% and 4%, respectively. The riskiest countries were China, the Russian Federation,

[2] Among the environmental quality indicators, i.e., GHG emissions, water pollution and forest cover, we have data on the contribution of each industry to GHG emissions and water pollution.

United States and Canada in 2000 and 2005. China was the riskiest country in 2005, with its emissions and water pollution levels being the highest among all countries in 2005. For the Russian Federation and Canada land without forest has been the major contributor. Finally, the United States were characterized by very high levels of emissions and land without forest in those years.

Secondly, over time SD comparisons for GHG emissions, water pollution and forest cover give insights of the progress of environmental quality between 1990 and 2010. 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 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. Overall, 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. For water pollution and its sub-industry contributors, there has not been a general increase between 1995 and 2005. However, we find that total water pollution has increased within 10 years in the second-order sense at the 10% significance level. Finally, there has been no clear indication of a change in land cover, since no significant stochastic dominance of any order has been obtained for forest cover for the period 1990 and 2010.

The third set of findings consists of detailed industry comparisons for emissions and water pollution. 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 always been the major contributor followed by the energy sector from 1990 to 2005. Overall, the major industries contributing to emissions have always been the same for the period between 1990 and 2005. However, there has been a gradual change in industry contributions to water pollution. In 1995, we find that the chemical, textile and food industries were the major contributors to water pollution dominating the rest, such as clay and glass, metal, paper, and wood industries. Yet in 2000, textile and food industries were the major water polluting industries dominating the chemical industry and finally in 2005, the food industry was the major water polluting industry dominating the rest including textiles and chemicals. These findings are consistent with the fact that the components that are assigned high weights in the SD approach are the ones which are the driving (fast-moving) variables in the sub-indices of GHG emissions and water pollution. Finally, the way these industries evolve over time with respect to environmental quality 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 index. Section 2 describes the pair-wise SD methodology from BD (2003), which is employed for over time and sub-industry comparisons. Section 4 discusses the data and the empirical results 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 quality index and each separate sub-index, constructed from GHG emissions, water pollution and land without forest cover. 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 equally weighted environmental risk index $(\boldsymbol{\tau})$, which is taken as an arbitrary 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 environmental composite risk 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. Let us denote by $G(z, \boldsymbol{\lambda}; F)$ the cdf of the composite index value $\boldsymbol{\lambda}'\boldsymbol{Y}$ at point z given by $G(z, \boldsymbol{\lambda}; F) := \int_{\mathbb{R}^n} \mathbb{I}\{\boldsymbol{\lambda}'\boldsymbol{u} \leq z\} dF(\boldsymbol{u})$.

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 index λ constructed from the set of components, or risk factors, 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 index λ exists, such that for some z, $\mathcal{J}_j(z,\tau;F)$ 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 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 index λ dominates the distribution of the benchmark (with fixed weights) index τ stochastically at first order (SD1) if, for any risk level z, $G(z,\tau;F) \geq G(z,\lambda;F)$. If z denotes a risk level, then the previous inequality implies that the proportion of countries in the distribution λ with value of risk 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 risk in τ than in λ. We can test whether an equally weighted risk index is optimal, or whether we can construct a composite index $\boldsymbol{\lambda}$ from the set of the risk components in the respective index that dominates the index.

The general hypotheses for testing the optimality of equally weighted risk index $\boldsymbol{\tau}$ 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:

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

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.

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 risk 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 component weights to be unity, while inequality (1e) disallows for negative weights.

This formulation allows us to test the dominance of the equally weighted risk index ($\boldsymbol{\tau}$) over any potential linear combination $\boldsymbol{\lambda}$ of the risk factors that are in the respective index. For more complex formulations we refer to Scaillet Topalaglou (2010) where tractable formulations and details on practical implementation are provided.

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 variable over two points in time. In particular, we examine the stochastic dominance of the GHG emissions, water pollution and forest cover over ten to twenty year period (from 1990 to 2005 for GHG emissions, from 1995 to 2005 for water pollution, from 1990 to 2010 for the forest cover) and determine whether there has been a deterioration or improvement in each environmental quality indicator over time. Additionally, SD pair-wise test are employed for the sub-industry comparisons for GHG emissions and water pollution. In other words, we find major contributing industries to emissions and water pollution at a given time. In this case we have a pair-wise comparison of a given environmental quality indicator over two points in time (or sub-industry contribution at a given time), such as the CO_2 emissions in year 1990 and in year 1995 (or electricity and heat production sector and transport sector contribution to CO_2 emissions in 1990). Take , for example, GHG emissions[3]. We define $G(z, F)$ the *cdf* of the emissions at point 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 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.

There is no guarantee that SD2 will hold, so one may want to look for third-order dominance. Third-order stochastic dominance ($SD3$) of F_1 over F_2 corresponds to $\mathcal{J}_3(z, F_1) \leq \mathcal{J}_3(z, F_2)$ 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 satisfies $U'(z) \geq 0$, $U''(z) \leq 0$, and $U'''(z) \geq 0$. This is the case of third-order stochastic dominance and it is equivalent to imposing the condition that it places a higher weight on lower levels of emissions.

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

[3]For simplicity, hereafter we discuss the pair-wise SD tests for emission comparisons over time; however, pair-wise tests will be applied to over time comparisons for other environmental quality indicators and also to sub-industry comparisons at a given time.

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

3.0.1 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:

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

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

$$\zeta_j(z; \widehat{F}_1) = \frac{1}{N}\sum_{i=1}^{N} \zeta_j(z; \mathbb{I}_{X_i}) = \frac{1}{N}\sum_{i=1}^{N} \frac{1}{(j-1)!}\mathbb{I}(X_i \leq z)(z - X_i)^{j-1} \quad (2)$$

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

The asymptotic properties of the tests are given 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, for bootstrapping methods).

4 Empirical Analysis

4.1 Data and Descriptive Statistics

The data set used in this paper consists of GHG emissions, water pollution and forest cover for several countries in various years, between 1990 and 2010[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., China has not released data for water pollution in 2000), which implies that only countries whose data are available for all variables will be ranked in the overall index. A detailed description of all the variables used and the normalization procedure is in Appendix I. In Section 4.2 two sub-indices for emissions and water pollution together with the overall composite index of environmental quality, and the ranking for different countries are provided. In Section 4.3 we present over time SD comparisons of the different environmental quality dimensions and further we compare different sub-industries to uncover the major contributors to GHG emissions and water pollution. The results for pair-wise SD comparisons are given in Tables A1 to A10 of Appendix II for space limitations[6].

4.2 SD efficient environmental quality index

This section presents our findings of the test for SD1 efficiency of each sub-index (i.e., GHG emissions and water pollution) and overall environmental quality index. We find that arbitrary weights are not optimal. We compute the weighting scheme of each respective factor in each sub-index, which offers the riskiest environment for the various countries.

The variables used for emissions are: CO_2, methane (CO_2 equivalent), nitrous oxide (CO_2 equivalent), other greenhouse gas emissions (CO_2 equivalent),

[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. We have annual data for water pollution from 1986 to 2007. Finally, forest cover data are avilable for years 1990, 1995, 2000, 2005 and 2010.

[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 A1 to A10 is summarized in the text and can be removed to conserve space. They can become available from the authors.

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).

We proceed to construct many other hybrid composites λ consisting of the four components of emissions listed above (CO_2, methane, nitous oxide, other greenhouse gas emissions) that stochastically dominate the equally weighted risk outcome τ, in the first order sense (e.g. for which $G(z, \tau; F) > G(z, \lambda; F)$). There are 514 different such composite λ's. Table 1 summarizes the results, presenting the average weights of the 514 hybrid composites that dominate the equally weighted risk outcomes. The inefficiency of the equally weighted risk index indicates that it is suboptimal. Our findings show that CO_2 is the main contributor to emissions with a 67.9% contribution followed by methane, nitrous oxide and other greenhouse gas emissions with 31.6%, 0.4% and 0.1% weights, respectively.

Then, we examine water pollution. The variables used for water pollution refer to yearly data from 1986 to 2007 in an unbalanced data set for 101 countries. They include organic water pollutant emissions (kg per day) expressed as percentage of organic water polluted by specific industries (i.e., chemical industry, clay and glass industry, food industry, metal industry, paper and pulp industry, wood industry, textile, other industries). We proceed to construct many other hybrid composites λ consisting of the eight components of water pollution listed above that stochastically dominate the equally weighted risk outcome τ, in the first order sense (e.g. for which $G(z, \tau; F) > G(z, \lambda; F)$). There are 949 different such composite λ's. Table 2i summarizes the results, presenting the average weights of the 949 hybrid composites that dominate the equally weighted risk outcomes.Our findings show that other industries and food industry contribute with 55.1% and 32.9% respectively. If other industries were removed, then food industry and textile industry would contribute with 66.0% and 29.2% respectively (see Table 2ii).

With the previous two indices, one can obtain the total GHG emissions and water pollution by adding each sub-components' contribution. However, one can also obtain the average contribution of emissions for CO_2, methane, nitrous and the other GHG emissions. Similarly, one can obtain the average contributions of the various components of water pollution. 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 and water pollution, as clearly not each country contributes equally (e.g., 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.

Finally, we consider forest resources, to include the depuration activity, water filtration, erosion control etc. that forests provide. In order to be consistent with the other sub-indices, total values of forest cover (km. square) are used in this sub-index. According to the World Bank definition, greenhouse (CO_2) emissions measured in kilotons (kt) that are stemming from the burning of fossil fuels and the manufacture of cement. They include contributions to the carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. CO_2 is a stable gas which is not transformed chemically in the atmosphere. However, some CO_2 is removed from the atmosphere by a natural process that includes the effect of vegetation, soils and oceans. Moreover, human activities such as reforestation, deforestation or land management may increase or decrease the amount of CO_2 removed from the atmosphere[7]. Forests act as natural filters that remove CO_2 from the atmosphere and as such their absence would affect negatively environmental quality. Since the other two environmental quality indicators (i.e., GHG emissions and water pollution) are affecting the environment negatively, we use the land without forests (expressed in square kilometer for each country) to evaluate the contribution of forests in the composite index. Clearly, higher land without forests concentrations imply lower CO_2 removal rates. Now we have three sub-indices, that is, the greenhouse emissions, the water pollution and the land without forest. The normalization of each sub-index is achieved by dividing each country's value in each index by the highest total value in that index.

Table 3 is obtained combining the three sub-indices to find the optimal weighting scheme for each sub-index. Table 4 provides the rankings of the various countries in terms of the composite index for years 2000 and 2005[8]. Our findings suggest that land without forest contributes the most with around 71%, greenhouse emissions contribute with around 25% and water pollution contributes with 4%. We can observe that the ranking remains more or less stable over the years. As argued above, higher land without forests concentrations imply lower CO_2 removal rates, since forests act as natural filters that remove CO_2 from the atmosphere. This explains the fact that land without forests contributes the most to the overall index as it is the overwhelming factor for the lack of CO_2 removal. On average, the countries with higher values of the composite index are the China, Russian Federation, the United States and Canada, but also other countries, such as Kazakhstan, Argentina, Saudi Arabia, Iran Islamic Republic, Mongolia and South Africa, are ranked as risky countries as far as the environmental quality is concerned[9]. Furthermore, we observe that

[7] For example, the global natural CO2 removal rate for the set of countries that we examine has been estimated to be around 60 percent for the period 1990 to 2000, see IPCC, 2000. See http://unfccc.int/ghg_emissions_data/predifined_qeuries/items/3814.php

[8] We have overlapping data for 1990, 1995, 2000 and 2005 for all environmental quality indicators. We only reported 2000 and 2005 rankings for two reasons. We have only 8 overlapping countries in 1990, therefore we have not reported the ranking in that year. On the other hand, even though 1995 consists of 42 overlapping countries, we do not have data for water pollution data for major countries, United States, Russian Federation and China.

[9] Canada is not in the rankings in 2000 and China is not in the rankings in 2005 since both countries lack data for those years for water pollution.

among the 59 countries for which we have full information for 2000 and 2005, we had 41 countries for which environmental quality deteriorated, while for the remaining 18 it improved over the same period. Therefore, there had been an overall deterioration in the environmental quality. Table 5 summarizes the changes between 2000 and 2005 for the countries for which we have full information. For some countries we only have partial information and hence they are not used in this comparison. For example Canada misses information for water pollution in 2005. Deterioration over time was mainly driven by the increase in the GHG emissions. All countries except Eritrea experienced an increase in their total GHG emissions. In addition, some countries experienced also an increase in their water pollution which reinforced the deterioration in their environmental quality even though their forest cover improved (e.g., Turkey and Vietnam). On the other hand, improvements for Germany, United Kingdom and Belgium were mainly driven by the decrease in total emissions and water pollution. Finally, the United States, Sweden and Japan improved their environmental quality mostly due to their decrease in water pollution even though they experienced an increase in their emissions.

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[10]), 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 4 remained substantially stable over the two periods. Notice that the following countries have the highest values of the overall environmental quality: China, the Russian Federation, the United States, Canada. This list does not overlap with the groups of countries adopted by the Kyoto Protocol - in particular, China and the Russian Federation are the heaviest polluters in our rankings. We observe that Sweden and the United States experienced an increase in the total emission levels from 2000 to 2005, but they increased their forest cover in the same period. Thus, the increase in forest cover allowed them to counter-balance their failure to meet their CO_2 targets, since forest cover offers a natural process to remove emissions from the atmosphere.

We also conducted ranking comparisons of our environmental quality index with the ESI rankings (see Esty et al. 2005) in 2005. ESI integrated 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

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

index combining them with equal weights for 146 countries. ESI gives scores between 0 and 100 and a higher index value represents a better environmental conditions for a country. Since our index represents the riskiest environmental quality, we converted the ESI measure by subtracting its score from 100 to represent ESI ranking from the riskiest to the least risky country to compare the two rankings. The first panel of Table 6 presents the rankings of the overlapping 61 countries in both rankings. The rankings differ significantly, especially when it comes to the environmentally riskiest countries. Even tough, ESI covers 21 indicators, yet they do not capture total contributions but are normalized with per capita or percentage values. Moreover, ESI does not cover land without forest and water pollution values. The second panel of Table 6 presents Spearman correlations between ESI rankings and our overall environmental quality index and its sub-components. We find that our overall environmental quality index without forest land has been positively and significantly correlated with the ESI rankings at the 1% significance level. However, there has been no significant correlation between total water pollution and the ESI rankings.

Even though there exist a significant and positive correlation between our environmental quality indices and the ESI rankings, there exist some major relative rank reversals. The riskiest five countries in our environmental risk index are China, the Russian Federation, the United States, Kazakhstan, and Saudi Arabia, whereas ESI ranked these countries as 4th, 44th, 37th, 24th and 3rd, respectively. Even though China and Saudi Arabia ranked in high positions in both rankings, the remaining countries experienced a lower ranking in ESI.

4.3 Pair-wise SD comparisons

In the next subsections over time pair-wise comparisons of emissions, water pollution and forest cover are discussed. Furthermore, we conduct SD pair-wise comparisons of GHG emissions to analyze which emission was the major contributor between 1990 and 2005. On the other hand, we find the major industries which contributed to the emissions and water pollution in the years 1990, 1995, 2000 and 2005. The results are presented in Tables A1 to A10 of Appendix II.

4.3.1 CO_2 emissions

First, we present the findings from the pair-wise SD comparisons of CO_2 emissions from 1990 to 2005. Panels of Table A1 and A2 present the results for SD1, SD2 and SD3 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 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., electricity and heat production) in 1995 dominate this component in 1990. Furthermore, we also test whether CO_2 emissions from each sub-fuel consumption (e.g., gaseous fuel consumption) in 1995 dominates its counterpart in 1990. These consecutive tests will allow us to analyze whether over time deteriorations (or improvements) have occurred in 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 A1 to A2 represents the years from 1995 to 2005 that are tested for stochastic dominance against years from 1990 to 2000. Percentage levels in the table represent the significance level of stochastic dominance (e.g., in the first panel of Table A1: 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 and third-order sense at the 5 percent level). NA represents that there is no dominance at that order.

The results from the first panel of Table A1 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 the fist panel of Table A1 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. The results for each sub-sector given from the second to the sixth panels of Table A1, 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, in three panels of Table A2 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.

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; and 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 A3 and A4 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. 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[11].

Finally, Table A4 presents 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 1% significance level. On the other hand, CO_2 emission from the solid fuel consumption dominate the emission from the gaseous fuel consumption at the second- and third-order sense at 10% significance level in 1990 and 2005 but the relationship between these two types of fuel consumption is ambiguous in 1995 and 2000.

4.3.2 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 total methane emissions, methane emissions from the agriculture and the energy sectors 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-sector are found between the same period[12].

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. Table A5 presents the findings for the years 1990 to 2005 with 5-year increments. Methane emissions from the agriculture sector dominates the energy sector at the first-order sense at 1% significance level.

4.3.3 Nitrous emissions

In this section, we present the pair-wise SD applications for the nitrous emissions from 1990 to 2005. We analyze the progress of total nitrous emissions, nitrous 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 emissions nor the nitrous 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 emissions over time. For the whole period, nitrous emissions from the agriculture sector

[11] 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.

[12] 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.

has always been higher than the other two sectors, while nitrous emissions from the energy sector have always been higher than the industrial sector for the whole period. Table A6 presents the findings for the years 1990 to 2005 with 5-year increments. Nitrous emissions from the agriculture sector dominate the energy and the industrial sectors at the first-order sense at 1% significance level and similarly 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.

4.3.4 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, we apply the same procedure to the former as we did with the latter We conduct pair-wise SD comparisons for the other GHG emissions and its sub-components from 1990 to 2005. The four panels of Table A7 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[13].

4.3.5 Comparison between GHG emissions

Finally, we present the pair-wise SD comparisons between CO_2, methane, nitrous and other GHG emissions in 1990, 1995, 2000 and 2005. The four panels of the Table A8 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. Furthermore, methane emissions dominate the nitrous 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. 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. These findings are consistent with the fact that the components that are assigned higher weights in the SD approach (CO_2 emissions and, subsequently,

[13] 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.

methane emissions) are the ones which are the driving (fast-moving) variables in the sub-index of GHG emissions constructed in Section 4.2 (Table 1). This result can help identify policies for achieving improvements in environmental quality.

4.4 Water pollution

For water pollution, we have followed a similar approach but the application period now only consists of a 10-year horizon (from 1995 to 2005)[14]. The eight panels of Table A9 give the pair-wise SD test results for the evolution of total water pollution and its sub-industries' contributors over time. The first panel of Table A9 suggests that there was no general increase in water pollution over the whole period. However, there has been an increase in water pollution in the 10-year horizon in a second-order sense suggesting that total water pollution has increased in this period for some but not for all countries. Similarly to total water pollution, there has been no general improvement in sub-industry water pollution over the whole period since there has been no dominance in the first-order sense for all industries. However, water pollution from different industries have shown different progress over time. Water pollution from chemical, food and wood industries increased between 1995 and 2000 in the second-order sense. Furthermore, chemical, food, wood, metal, and clay and glass industries increased between 1995 and 2005 in the second-order sense. Finally, no dominance of any order is found for textile and paper and pulp industries. Therefore, one can conclude that the increase in water pollution over time is mostly driven by the chemical, food and wood industries.

Secondly, we analyze the sub-industry contibutions to the water pollution in 1995, 2000 and 2005. The three panels of Table A10 present all possible pair-wise comparisons between sub-industry water pollutions in 1995, 2000 and 2005 respectively. In 1995 the chemical industry pollutes water more than the clay and glass, metal and wood industries (i.e., in the first panel of Table A10, chemical industry water pollution stochastically dominates the clay and glass metal and wood industries in the first-order sense at the 10%, 10% and 1% significance level respectively). Furthermore, water pollution from food and textile industries has been more than pollution from the clay and glass, metal, paper and wood industries in 1995. Finally, in 1995, the clay and glass industry was responsible for water pollution more than the metal industry and paper industry polluted more than the wood industry. Any further comparisons have not suggested any further dominance. Clearly, in 1995, chemical, textile and food industries were the major contributors to water pollution.

In 2000, the majority of the dominance relation between industries remained the same but there were some differences with respect to 1995. Water pollution from the chemical industry in 2000 dominates pollution from the paper industry. On the other hand, water pollution from the food industry dominates the

[14] There has been information on water pollution in 1990 for only 12 countries which makes the application impossible before 1995 since the power of tests would not have been reliable.

pollution from the chemical industry. Therefore, in 2000, the major contributors to water pollution is the food and textile industries. Finally, in 2005, water pollution from the food industry contributes more than the any other industry (i.e, water pollution from the food industry dominates such pollution from any industry in the first-order sense).

Overall, not only there has been an increase in water pollution from food and chemical industries in a second-order sense over time in a 5-year horizon but also those industries have been the major water polluters when compared with other industries. Finally, the food industry has been gradually become the major contributor to water pollution, dominating the rest.

Observe that these findings are consistent with the fact that the components that are assigned higher weights in the SD approach are the ones which are the driving (fast-moving) variables in the sub-index of water emissions constructed in Section 4.2 (Table 2i and Table 2ii).

4.5 Forest area

Finally, even though, forest cover has been mostly constant for certain countries, there has been also major changes over time for some other countries. For example, there has been a major increase in the forest cover of China and United States between 1990 and 2010. In 1990, the forest cover of China and United States were 1571410 and 2963350 square kilometers, but in 2010, forest cover in both countries increased to 2068610 and 3040220 square kilometers respectively. On the other hand, for example, Brazil's forest cover decreased by 553170 square kilometers in the same period. Therefore, we conduct SD tests to analyze whether there exists any SD ordering of the evolution of forest cover between 1990 and 2010 where we find no clear SD orderings over time. Therefore, there has been no clear progress that we detect in forest cover. Forest cover for some countries increased whereas it decreased for some others and as a result the total area covered has remained mainly stable overall.

5 Conclusion

In this paper, we present consistent tests for SD with dependent data. Our main result is the derivation of an optimal index for the environmental quality of a country based on SD analysis with differential component weights. This index will offer the maximum level of environmental risk in a country for a given probability level and also be the least volatile over time among its set of competitors. When GHG emissions, water pollution and forest cover are considered for overall environmental quality index, , land without forest contributes the most with a weight of 71% and the contribution of emissions and water pollution are being 25% and 4%, respectively. The results underscore the importance of forests to act as natural filters that remove CO_2 from the atmosphere. We then proceed to rank countries according to their index of environmental quality and their rankings are compared with those of the Kyoto Protocol and ESI.

Furthermore, we employ consistent pair-wise SD tests to examine the dynamic progress of GHG emissions (i.e., CO_2, methane, nitrous and other GHG emissions), water pollution and forest cover over time. 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 between 1990 and 2005. For water pollution, we find that total water pollution has increased within 10 years in a second-order sense. We also conduct pair-wise SD tests which allow us to analyze the major industry contributors to the emissions and water pollution at any given time. 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. In addition, there has been a gradual change of industry contributions to water pollution. We find that the chemical, textile and food industries were the major contributors in 1995 whereas in 2000, textile and food industries were the major water polluting industries. Finally, in 2005, the food industry has become the major industry polluting water as water pollution from this industry dominated pollutions from any other industry.

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 optimal composite index representing a most appropriate measure of wealth for a country. One could find the weighting scheme of each sub-index (i.e. of environmental quality, of natural resources, and HDI) which corresponds to the overall riskiest case for all countries. 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 can be seen as complementary to the seminal works on genuine saving and sustainable development by Dasgupta (2001), Arrow et al (2003, 2004, 2010).

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Table 1: Stochastic efficient weighting for greenhouse 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	0.679	0.316	0.004	0.001

Table 2i: Stochastic efficient weighting of industries for organic water pollution									
Number of observations	Number of dominating weighting schemes	Chemical industry	Clay and glass industry	Food industry	Metal industry	Paper and pulp industry	Textile industry	Wood industry	Other industries
N	**N**	***Average of dominating weighting schemes***							
967	949	0.003	0.002	0.329	0.000	0.000	0.115	0.000	0.551

Table 2ii: Stochastic efficient weighting of industries for organic water pollution (except other)								
Number of observations	Number of dominating weighting schemes	Chemical industry	Clay and glass industry	Food industry	Metal industry	Paper and pulp industry	Textile industry	Wood industry
N	**N**	***Average of dominating weighting schemes***						
967	967	0.035	0.003	0.660	0.006	0.004	0.292	0.000

Table 3: Stochastic efficient weighting of sub-indices (Greenhouse emissions, water pollution, land without forest)				
Number of observations	Number of dominating weighting schemes	Greenhouse emissions	Water pollution	Land without forest
N	**n**	***Average of dominating weighting schemes***		
183	165	0.251	0.040	0.709

Table 4: Environmental quality rankings in 2000 and 2005

Country	Environmental index outcome in 2000	N	Country	Environmental index outcome in 2005
Russian Fed.	0.7867	**1**	China	0.9234
United States	0.7522	**2**	Russian Fed.	0.7910
Canada	0.5358	**3**	United States	0.7515
Kazakhstan	0.2342	**4**	Kazakhstan	0.2363
Argentina	0.2168	**5**	Saudi Arabia	0.1969
Iran, Islamic Rep.	0.1460	**6**	Iran, Islamic Rep.	0.1501
South Africa	0.1136	**7**	Mongolia	0.1238
Indonesia	0.0906	**8**	South Africa	0.1155
Ethiopia	0.0764	**9**	Indonesia	0.0966
Turkey	0.0680	**10**	Ethiopia	0.0774
Japan	0.0598	**11**	Turkey	0.0692
Ukraine	0.0581	**12**	Japan	0.0595
Germany	0.0575	**13**	Ukraine	0.0580
France	0.0532	**14**	Germany	0.0562
Colombia	0.0471	**15**	France	0.0535
Yemen, Rep.	0.0455	**16**	Chile	0.0532
United Kingdom	0.0431	**17**	Colombia	0.0476
Bolivia	0.0426	**18**	Tanzania	0.0475
Spain	0.0417	**19**	Yemen, Rep.	0.0458
Thailand	0.0389	**20**	Spain	0.0435
Botswana	0.0381	**21**	United Kingdom	0.0418
Italy	0.0376	**22**	Botswana	0.0386
Morocco	0.0358	**23**	Italy	0.0379
Poland	0.0331	**24**	Morocco	0.0361
Oman	0.0276	**25**	Poland	0.0333
Vietnam	0.0225	**26**	Oman	0.0282
Korea, Rep.	0.0205	**27**	Philippines	0.0246
Norway	0.0205	**28**	Vietnam	0.0244
Romania	0.0193	**29**	Korea, Rep.	0.0213
Syrian Arab Rep.	0.0182	**30**	Norway	0.0202
New Zealand	0.0181	**31**	Romania	0.0196
Malaysia	0.0164	**32**	Malaysia	0.0192
Kyrgyz Republic	0.0160	**33**	Syrian Arab Rep.	0.0183
Sweden	0.0144	**34**	New Zealand	0.0181
Ecuador	0.0125	**35**	Kyrgyz Republic	0.0160
Tajikistan	0.0119	**36**	Ecuador	0.0138
Netherlands	0.0101	**37**	Sweden	0.0137
Czech Republic	0.0098	**38**	Tajikistan	0.0119
Finland	0.0094	**39**	Greece	0.0118
Senegal	0.0094	**40**	Netherlands	0.0100
Bulgaria	0.0090	**41**	Finland	0.0097
Hungary	0.0089	**42**	Czech Republic	0.0097
Azerbaijan	0.0085	**43**	Hungary	0.0089
Portugal	0.0081	**44**	Azerbaijan	0.0087
Jordan	0.0081	**45**	Bulgaria	0.0087

Ireland	0.0077	**46**	Jordan	0.0084
Eritrea	0.0074	**47**	Portugal	0.0081
Belgium	0.0069	**48**	Ireland	0.0076
Austria	0.0067	**49**	Eritrea	0.0075
Denmark	0.0056	**50**	Austria	0.0071
Lithuania	0.0045	**51**	Belgium	0.0066
Slovak Republic	0.0043	**52**	Denmark	0.0055
Croatia	0.0042	**53**	Lithuania	0.0045
Israel	0.0042	**54**	Croatia	0.0043
Panama	0.0038	**55**	Slovak Republic	0.0042
Latvia	0.0030	**56**	Panama	0.0039
Moldova	0.0029	**57**	Qatar	0.0032
Qatar	0.0025	**58**	Latvia	0.0030
Estonia	0.0024	**59**	Moldova	0.0029
Singapore	0.0021	**60**	Estonia	0.0024
Macedonia, FYR	0.0020	**61**	Albania	0.0020
Albania	0.0019	**62**	Macedonia, FYR	0.0019
Trinidad & Tobago	0.0015	**63**	Slovenia	0.0015
Slovenia	0.0014	**64**	Cyprus	0.0010
Cyprus	0.0009	**65**	Luxembourg	0.006
Luxembourg	0.0005	**66**	Malta	0.0001
Malta	0.0001	**67**		

Table 5: Change in environmental quality outcome between 2000 and 2005

Country	Deterioration +		Country	Improvement -
Indonesia	6044		United Kingdom	1323
Russian Fed.	4210		Germany	1251
Iran, Islamic Rep.	4045		Sweden	684
Malaysia	2849		United States	657
Kazakhstan	2069		Belgium	326
South Africa	1990		Japan	285
Vietnam	1859		Bulgaria	271
Spain	1849		Norway	251
Ecuador	1281		Denmark	149
Turkey	1210		Czech Republic	115
Ethiopia	941		Netherlands	110
Korea, Rep.	807		Macedonia, FYR	86
Qatar	753		Ukraine	84
Oman	629		Slovak Republic	43
Botswana	557		Hungary	21
Colombia	534		Lithuania	21
Austria	379		Portugal	14
Yemen, Rep.	343		Ireland	12
Finland	334			
France	298			
Italy	298			
Romania	259			
Morocco	241			
Jordan	239			
Azerbaijan	212			
Poland	188			
Luxembourg	103			
Croatia	101			
New Zealand	92			
Panama	86			
Syrian Arab Rep.	83			
Estonia	55			
Slovenia	39			
Moldova	37			
Albania	36			
Cyprus	31			
Latvia	27			
Malta	23			
Eritrea	15			
Tajikistan	11			
Kyrgyz Republic	2			

Note: All deteriorations and improvements are multiplied by million to express them precisely.

Table 6: Comparison between environmental quality and ESI rankings in 2005

Panel A: Ranking of countries with environmental index and ESI score

Country	Environmental index outcome in 2005	**N**	Country	ESI score
China	0.9234	**1**	Yemen, Rep.	62.7
Russian Fed.	0.7910	**2**	Ethiopia	62.2
United States	0.7515	**3**	Saudi Arabia	62.2
Kazakhstan	0.2363	**4**	China	61.4
Saudi Arabia	0.1969	**5**	Tajikistan	61.4
Iran, Islamic Rep.	0.1501	**6**	Iran, Islamic Rep.	60.2
Mongolia	0.1238	**7**	Philippines	57.7
South Africa	0.1155	**8**	Vietnam	57.7
Indonesia	0.0966	**9**	Korea, Rep.	57.0
Ethiopia	0.0774	**10**	Syrian Arab Rep.	56.2
Turkey	0.0692	**11**	Belgium	55.6
Japan	0.0595	**12**	Ukraine	55.3
Ukraine	0.0580	**13**	Morocco	55.2
Germany	0.0562	**14**	Poland	55.0
France	0.0535	**15**	Azerbaijan	54.6
Chile	0.0532	**16**	Romania	53.8
Colombia	0.0476	**17**	South Africa	53.8
Tanzania	0.0475	**18**	Czech Republic	53.4
Yemen, Rep.	0.0458	**19**	Turkey	53.4
Spain	0.0435	**20**	Macedonia, FYR	52.8
United Kingdom	0.0418	**21**	Jordan	52.2
Botswana	0.0386	**22**	Oman	52.1
Italy	0.0379	**23**	Kyrgyz Republic	51.6
Morocco	0.0361	**24**	Kazakhstan	51.4
Poland	0.0333	**25**	Indonesia	51.2
Oman	0.0282	**26**	Spain	51.2
Philippines	0.0246	**27**	Bulgaria	51.0
Vietnam	0.0244	**28**	Mongolia	51.0
Korea, Rep.	0.0213	**29**	Greece	49.9
Norway	0.0202	**30**	Italy	49.9
Romania	0.0196	**31**	United Kingdom	49.8
Malaysia	0.0192	**32**	Tanzania	49.7
Syrian Arab Rep.	0.0183	**33**	Moldova	48.8
New Zealand	0.0181	**34**	Hungary	48.0
Kyrgyz Republic	0.0160	**35**	Ecuador	47.6
Ecuador	0.0138	**36**	Slovak Republic	47.2
Sweden	0.0137	**37**	United States	47.0
Tajikistan	0.0119	**38**	Chile	46.4
Greece	0.0118	**39**	Netherlands	46.3
Netherlands	0.0100	**40**	Malaysia	46.0
Finland	0.0097	**41**	Portugal	45.8
Czech Republic	0.0097	**42**	France	44.8
Hungary	0.0089	**43**	Botswana	44.1

Azerbaijan	0.0087	**44**	Russian Fed.	43.9
Bulgaria	0.0087	**45**	Germany	43.0
Jordan	0.0084	**46**	Japan	42.7
Portugal	0.0081	**47**	Slovenia	42.5
Ireland	0.0076	**48**	Panama	42.3
Eritrea	0.0075	**49**	Denmark	41.8
Austria	0.0071	**50**	Estonia	41.8
Belgium	0.0066	**51**	Albania	41.2
Denmark	0.0055	**52**	Colombia	41.1
Lithuania	0.0045	**53**	Lithuania	41.1
Croatia	0.0043	**54**	Ireland	40.8
Slovak Republic	0.0042	**55**	Croatia	40.5
Panama	0.0039	**56**	Latvia	39.6
Qatar	0.0032	**57**	New Zealand	39.0
Latvia	0.0030	**58**	Austria	37.3
Moldova	0.0029	**59**	Sweden	28.3
Estonia	0.0024	**60**	Norway	26.6
Albania	0.0020	**61**	Finland	24.9

Panel B: Spearman rank correlation between environmental quality index and ESI score in 2005

Spearman rank correlation between ESI and optimal environmental risk indices					
	ESI Score	Total emissions index	Water pollution index	Forestless land index	Overall Environmental index
ESI score	1				
Total emissions index	0.2446***	1			
Water pollution index	0.1406	0.9053*	1		
Forestless land index	0.3780*	0.5204*	0.3592*	1	
Overall environmental index	0.3968*	0.6924*	0.5272*	0.9471*	1
Note: 61 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 I

Greenhouse emissions

Variables used: CO_2, Methane (CO_2 equivalent), Nitrous oxide (CO_2 equivalent), other greenhouse gas emissions (CO_2 equivalent)

Industries:

a) Industries contributing to Co_2 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

Data Set:

Co_2 emissions consist of unbalanced data set (annual data between 1960 and 2008) and having Co_2 emission values for 198 countries in 2008

Methane, nitrous oxide and other greenhouse emissions (all measured in Co_2 equivalent) have data in 1990, 1995, 2000, and 2005 (balanced data for 135 countries)

Overlapping data for all type of greenhouse emissions consist years 1990 (110 countries), 1995 (134 countries), 2000 (135 countries) and 2005 (135 countries) in total of 514 observations.

Water pollution

Case 1: All industries included

Case 2: All industries included expect other industries

Variables used: Organic water pollutant (BOD) emissions (kg per day), Organic water polluted by specific industry measured as kg per day.

Industries: Chemical industry, clay and glass industry, food industry, metal industry, paper and pulp industry, wood industry, textile, other)

Other industries are treated as residual to capture remaining percent of the total water pollution.

Data Set: Unbalanced data set for 101 countries from 1986 to 2007 (yearly) consisting of 967 observations.

Overall environmental quality index

Variables used:

Total greenhouse emissions (Co2 equivalent), Water pollution (kg per day), Land without forest (km. square)

Overlapping data consist of unbalanced data for years 1990 (8 countries), 1995 (42 countries), 2000 (67 countries) and 2005 (66 countries) in total of 183 observations.

Normalization procedure:

Total greenhouse (GHG) emissions:

Co2, methane, nitrous and other GHG emissions are aggregated for 1990, 1995, 2000 and 2005 to have the total greenhouse emissions for each country. Highest total greenhouse emission is used to normalize the total greenhouse emissions (i.e., China in 2005).

Total water pollution:

Total organic water pollutant emissions (kg per day) are used and the highest total water pollution is used to normalize the water pollution (i.e., China in 2005).

Total land without forest:

Total land without forest is used (i.e., total land area in km. square minus the forest area in km. square). The highest total land without forest is used to normalize the land without forest in all countries (i.e., Russian Federation in 2005).

Appendix II

Pair-wise SD results from over time and sub-industry comparisons

Table A1: Total and sub-industry Co2 emissions between 1990 and 2005

i) Co2 emissions (Total)						ii) CO2 emissions from electricity and heat production				
		1990	1995	2000				1990	1995	2000
1995	SD1	NA	-	-		1995	SD1	NA	-	-
	SD2	NA	-	-			SD2	NA	-	-
	SD3	NA	-	-			SD3	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
	SD3	NA	NA	-			SD3	NA	NA	-
2005	SD1	10%	NA	NA		2005	SD1	NA	NA	NA
	SD2	10%	NA	NA			SD2	NA	NA	NA
	SD3	5%	NA	NA			SD3	NA	NA	NA

iii) CO2 emissions from manufacturing industries and construction						iv) 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	-	-
	SD3	NA	-	-			SD3	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
	SD3	NA	NA	-			SD3	NA	NA	-
2005	SD1	NA	NA	NA		2005	SD1	NA	NA	NA
	SD2	NA	NA	NA			SD2	NA	NA	NA
	SD3	NA	NA	NA			SD3	NA	NA	NA

v) CO2 emissions from residential buildings and commercial and public services						vi) CO2 emissions from transport				
		1990	1995	2000				1990	1995	2000
1995	SD1	NA	-	-		1995	SD1	NA	-	-
	SD2	NA	-	-			SD2	NA	-	-
	SD3	NA	-	-			SD3	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
	SD3	NA	NA	-			SD3	NA	NA	-
2005	SD1	NA	NA	NA		2005	SD1	NA	NA	NA
	SD2	NA	NA	NA			SD2	NA	NA	NA
	SD3	NA	NA	NA			SD3	NA	NA	NA

Table A2: Sub-fuel Co2 emissions between 1990 and 2005

i) CO_2 emissions from gaseous fuel consumption						ii) CO_2 emissions from liquid fuel consumption				
		1990	1995	2000				1990	1995	2000
1995	SD1	NA	-	-		1995	SD1	NA	-	-
	SD2	NA	-	-			SD2	NA	-	-
	SD3	NA	-	-			SD3	NA	-	-
2000	SD1	NA	NA	-		2000	SD1	NA	NA	-
	SD2	NA	NA	-			SD2	NA	NA	-
	SD3	10%	NA	-			SD3	NA	NA	-
2005	SD1	5%	NA	NA		2005	SD1	NA	NA	NA
	SD2	5%	NA	NA			SD2	NA	NA	NA
	SD3	5%	NA	NA			SD3	NA	NA	NA

iii) CO_2 emissions from solid fuel consumption				
		1990	1995	2000
1995	SD1	NA	-	-
	SD2	NA	-	-
	SD3	NA	-	-
2000	SD1	NA	NA	-
	SD2	NA	NA	-
	SD3	NA	NA	-
2005	SD1	NA	NA	NA
	SD2	NA	NA	NA
	SD3	NA	NA	NA

Table A3: Sub-industry Co2 emission comparisons in 1990, 1995, 2000 and 2005

i) Sub-industry CO2 emission comparisons in 1990				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
EH versus **MC**	EH dominates MC	5%	5%	1%
EH versus **OT**	EH dominates OT	1%	1%	1%
EH versus **RC**	EH dominates RC	1%	1%	1%
EH versus **TR**	EH dominates TR	5%	5%	1%
MC versus **OT**	MC dominates OT	1%	1%	1%
MC versus **RC**	MC dominates RC	1%	1%	1%
MC versus **TR**	TR dominates MC	10%	10%	5%
OT versus **RC**	RC dominates OT	1%	1%	1%
OT versus **TR**	TR dominates OT	1%	1%	1%
RC versus **TR**	TR dominates RC	1%	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"				

ii) Sub-industry CO2 emission comparisons in 1995				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
EH versus **MC**	EH dominates MC	5%	5%	1%
EH versus **OT**	EH dominates OT	1%	1%	1%
EH versus **RC**	EH dominates RC	1%	1%	1%
EH versus **TR**	EH dominates TR	5%	5%	1%
MC versus **OT**	MC dominates OT	1%	1%	1%
MC versus **RC**	MC dominates RC	1%	1%	1%
MC versus **TR**	TR dominates MC	5%	5%	1%
OT versus **RC**	RC dominates OT	1%	1%	1%
OT versus **TR**	TR dominates OT	1%	1%	1%
RC versus **TR**	TR dominates RC	1%	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 A3 continued...

iii) Sub-industry CO2 emission comparisons in 2000				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
EH versus **MC**	EH dominates MC	5%	5%	1%
EH versus **OT**	EH dominates OT	1%	1%	1%
EH versus **RC**	EH dominates RC	1%	1%	1%
EH versus **TR**	EH dominates TR	10%	10%	10%
MC versus **OT**	MC dominates OT	1%	1%	1%
MC versus **RC**	MC dominates RC	1%	1%	1%
MC versus **TR**	TR dominates MC	5%	5%	1%
OT versus **RC**	RC dominates OT	1%	1%	1%
OT versus **TR**	TR dominates OT	1%	1%	1%
RC versus **TR**	TR dominates RC	1%	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"				

iv) Sub-industry CO2 emission comparisons in 2005				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
EH versus **MC**	EH dominates MC	1%	1%	1%
EH versus **OT**	EH dominates OT	1%	1%	1%
EH versus **RC**	EH dominates RC	1%	1%	1%
EH versus **TR**	EH dominates TR	5%	5%	1%
MC versus **OT**	MC dominates OT	1%	1%	1%
MC versus **RC**	MC dominates RC	1%	1%	1%
MC versus **TR**	TR dominates MC	5%	5%	1%
OT versus **RC**	RC dominates OT	1%	1%	1%
OT versus **TR**	TR dominates OT	1%	1%	1%
RC versus **TR**	TR dominates RC	1%	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 A4: Sub-fuel Co2 emission comparisons in 1990, 1995, 2000 and 2005

i) Sub-fuel CO2 emission comparisons in 1990				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
GAS versus **LIQUID**	LIQUID dominates	1%	1%	1%
GAS versus **SOLID**	SOLID dominates	NA	10%	10%
LIQUID versus **SOLID**	LIQUID dominates	1%	1%	1%
ii) Sub-fuel CO2 emission comparisons in 1995				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
GAS versus **LIQUID**	LIQUID dominates	1%	1%	1%
GAS versus **SOLID**	NA	NA	NA	NA
LIQUID versus **SOLID**	LIQUID dominates	1%	1%	1%
iii) Sub-fuel CO2 emission comparisons in 2000				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
GAS versus **LIQUID**	LIQUID dominates	1%	1%	1%
GAS versus **SOLID**	NA	NA	NA	NA
LIQUID versus **SOLID**	LIQUID dominates	1%	1%	1%
iv) Sub-fuel CO2 emission comparisons in 2005				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
GAS versus **LIQUID**	LIQUID dominates	1%	1%	1%
GAS versus **SOLID**	SOLID dominates	NA	10%	10%
LIQUID versus **SOLID**	LIQUID dominates	1%	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 A5: Sub-sector methane emission comparisons in 1990, 1995, 2000 and 2005

i) Sub-sector methane emission comparisons in 1990				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
ii) Sub-sector methane emission comparisons in 1995				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
iii) Sub-sector methane emission comparisons in 2000				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
iv) Sub-sector methane emission comparisons in 2005				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
Note: AGRI represents the methane emissions from "agricultural sector"; ENER represents the methane emissions from "energy sector"				

Table A6: Sub-sector nitrous emission comparisons in 1990, 1995, 2000 and 2005

i) Sub-sector nitrous emission comparisons in 1990				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
AGRI versus **INDUS**	AGRI dominates	1%	1%	1%
ENER versus **INDUS**	ENER dominates	1%	1%	1%
ii) Sub-sector nitrous emission comparisons in 1995				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
AGRI versus **INDUS**	AGRI dominates	1%	1%	1%
ENER versus **INDUS**	ENER dominates	1%	1%	1%
iii) Sub-sector nitrous emission comparisons in 2000				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
AGRI versus **INDUS**	AGRI dominates	1%	1%	1%
ENER versus **INDUS**	ENER dominates	1%	1%	1%
iv) Sub-sector nitrous emission comparisons in 2005				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
AGRI versus **ENER**	AGRI dominates	1%	1%	1%
AGRI versus **INDUS**	AGRI dominates	1%	1%	1%
ENER versus **INDUS**	ENER dominates	1%	1%	1%
Note: AGRI represents the nitrous emissions from "agricultural sector"; ENER represents the nitrous emissions from "energy sector"; INDUS represents the nitrous emissions from "industrial sector".				

Table A7: Other GHG, PFC, HFC and SF6 emissions over time between 1990 and 2005

i) Other GHG emissions (Total)						ii) PFC emissions				
		1990	1995	2000				1995	2000	2005
1995	SD1	1%	-	-		1990	SD1	5%	NA	1%
	SD2	1%	-	-			SD2	5%	NA	1%
	SD3	1%	-	-			SD3	5%	NA	1%
2000	SD1	1%	5%	-		1995	SD1	-	NA	NA
	SD2	1%	5%	-			SD2	-	NA	NA
	SD3	1%	1%	-			SD3	-	NA	NA
2005	SD1	1%	1%	NA		2000	SD1	-	-	NA
	SD2	1%	1%	NA			SD2	-	-	NA
	SD3	1%	1%	NA			SD3	-	-	NA

iii) HFC emissions						iv) SF6 emissions				
		1990	1995	2000				1990	1995	2000
1995	SD1	1%	-	-		1995	SD1	NA	-	-
	SD2	1%	-	-			SD2	NA	-	-
	SD3	1%	-	-			SD3	NA	-	-
2000	SD1	1%	1%	-		2000	SD1	NA	NA	-
	SD2	1%	1%	-			SD2	NA	NA	-
	SD3	1%	1%	-			SD3	NA	NA	-
2005	SD1	1%	1%	1%		2005	SD1	NA	NA	NA
	SD2	1%	1%	1%			SD2	NA	NA	NA
	SD3	1%	1%	1%			SD3	NA	NA	NA

Table A8: Pair-wise Co2, methane, nitrous and other GHG comparisons

i) Emission (Co2, methane, nitrous and other GHG) comparisons in 1990				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
Co2 versus **MET**	Co2 dominates	5%	5%	1%
Co2 versus **NIT**	Co2 dominates	1%	1%	1%
Co2 versus **OTH**	Co2 dominates	1%	1%	1%
MET versus **NIT**	Methane dominates	1%	1%	1%
MET versus **OTH**	Methane dominates	1%	1%	1%
NIT versus **OTH**	Nitrous dominates	1%	1%	1%
Note: Co2 represents the total Co2 emissions; MET represents the total methane emissions; NIT represents the total nitrous emissions; OTH represents the total other GHG emissions. All emissions are measured in same units as thousand metric tons of CO2 equivalent emissions.				

ii) Emission (Co2, methane, nitrous and other GHG) comparisons in 1995				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
Co2 versus **MET**	Co2 dominates	1%	1%	1%
Co2 versus **NIT**	Co2 dominates	1%	1%	1%
Co2 versus **OTH**	Co2 dominates	1%	1%	1%
MET versus **NIT**	Methane dominates	1%	1%	1%
MET versus **OTH**	Methane dominates	1%	1%	1%
NIT versus **OTH**	Nitrous dominates	1%	1%	1%
Note: Co2 represents the total Co2 emissions; MET represents the total methane emissions; NIT represents the total nitrous emissions; OTH represents the total other GHG emissions. All emissions are measured in same units as thousand metric tons of CO2 equivalent emissions.				

iii) Emission (Co2, methane, nitrous and other GHG) comparisons in 2000				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
Co2 versus **MET**	Co2 dominates	1%	1%	1%
Co2 versus **NIT**	Co2 dominates	1%	1%	1%
Co2 versus **OTH**	Co2 dominates	1%	1%	1%
MET versus **NIT**	Methane dominates	1%	1%	1%
MET versus **OTH**	Methane dominates	1%	1%	1%
NIT versus **OTH**	Nitrous dominates	1%	1%	1%
Note: Co2 represents the total Co2 emissions; MET represents the total methane emissions; NIT represents the total nitrous emissions; OTH represents the total other GHG emissions. All emissions are measured in same units as thousand metric tons of CO2 equivalent emissions.				

iv) Emission (Co2, methane, nitrous and other GHG) comparisons in 2005				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
Co2 versus **MET**	Co2 dominates	1%	1%	1%
Co2 versus **NIT**	Co2 dominates	1%	1%	1%
Co2 versus **OTH**	Co2 dominates	1%	1%	1%
MET versus **NIT**	Methane dominates	1%	1%	1%
MET versus **OTH**	Methane dominates	1%	1%	1%
NIT versus **OTH**	Nitrous dominates	1%	1%	1%
Note: Co2 represents the total Co2 emissions; MET represents the total methane emissions; NIT represents the total nitrous emissions; OTH represents the total other GHG emissions. All emissions are measured in same units as thousand metric tons of CO2 equivalent emissions.				

Table A9: Total and sub-industry water pollutions over time, between 1995 and 2005

i) Water pollution (Total)			
		1995	2000
2000	SD1	NA	-
	SD2	NA	-
	SD3	NA	-
2005	SD1	NA	NA
	SD2	10%	NA
	SD3	10%	NA

ii) Water pollution (Chemical industry)			
		1995	2000
2000	SD1	NA	-
	SD2	10%	-
	SD3	10%	-
2005	SD1	NA	NA
	SD2	10%	NA
	SD3	10%	NA

iii) Water pollution (Clay and glass industry)			
		1995	2000
2000	SD1	NA	-
	SD2	NA	-
	SD3	NA	-
2005	SD1	NA	NA
	SD2	10%	NA
	SD3	10%	NA

iv) Water pollution (Food industry)			
		1995	2000
2000	SD1	NA	-
	SD2	10%	-
	SD3	10%	-
2005	SD1	NA	NA
	SD2	5%	NA
	SD3	5%	NA

v) Water pollution (Metal industry)			
		1995	2000
2000	SD1	NA	-
	SD2	NA	-
	SD3	NA	-
2005	SD1	NA	NA
	SD2	10%	NA
	SD3	10%	NA

vi) Water pollution (Paper and pulp industry)			
		1995	2000
2000	SD1	NA	-
	SD2	NA	-
	SD3	NA	-
2005	SD1	NA	NA
	SD2	NA	NA
	SD3	NA	NA

vii) Water pollution (Textile industry)			
		1995	2000
2000	SD1	NA	-
	SD2	NA	-
	SD3	NA	-
2005	SD1	NA	NA
	SD2	NA	NA
	SD3	NA	NA

viii) Water pollution (Wood industry)			
		1995	2000
2000	SD1	NA	-
	SD2	10%	-
	SD3	10%	-
2005	SD1	NA	NA
	SD2	5%	NA
	SD3	5%	NA

Table A10: Sub-industry water pollution comparisons in 1995, 2000 and 2005

i) Water pollution sub-industry comparisons in 1995				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
Chemical versus Clay	Chemical dominates	10%	5%	5%
Chemical versus Food	NA	NA	NA	NA
Chemical versus Metal	Chemical dominates	10%	5%	1%
Chemical versus Paper	NA	NA	NA	NA
Chemical versus Textile	NA	NA	NA	NA
Chemical versus Wood	Chemical dominates	1%	1%	1%
Clay versus Food	Food dominates	1%	1%	1%
Clay versus Metal	Clay dominates	10%	10%	10%
Clay versus Paper	NA	NA	NA	NÀ
Clay versus Textile	Textile dominates	10%	1%	1%
Clay versus Wood	NA	NA	NA	NA
Food versus Metal	Food dominates	1%	1%	1%
Food versus Paper	Food dominates	10%	5%	5%
Food versus Textile	NA	NA	NA	NA
Food versus Wood	Food dominates	1%	1%	1%
Metal versus Paper	NA			
Metal versus Textile	Textile dominates	1%	1%	1%
Metal versus Wood	NA			
Paper versus Textile	Textile dominates	10%	5%	5%
Paper versus Wood	Paper dominates	5%	5%	5%
Textile versus Wood	Textile dominates	1%	1%	1%

Table A10 continued...

ii) Water pollution sub-industry comparisons in 2000				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
Chemical versus Clay	Chemical dominates	10%	5%	5%
Chemical versus Food	Food dominates	5%	5%	5%
Chemical versus Metal	Chemical dominates	5%	5%	1%
Chemical versus Paper	Chemical dominates	NA	NA	10%
Chemical versus Textile	NA	NA	NA	NA
Chemical versus Wood	Chemical dominates	1%	1%	1%
Clay versus Food	Food dominates	1%	1%	1%
Clay versus Metal	Clay dominates	10%	10%	10%
Clay versus Paper	NA	NA	NA	NÀ
Clay versus Textile	Textile dominates	5%	1%	1%
Clay versus Wood	NA	NA	NA	NA
Food versus Metal	Food dominates	1%	1%	1%
Food versus Paper	Food dominates	1%	1%	1%
Food versus Textile	NA	NA	NA	NA
Food versus Wood	Food dominates	1%	1%	1%
Metal versus Paper	Paper dominates	10%	10%	10%
Metal versus Textile	Textile dominates	1%	1%	1%
Metal versus Wood	NA			
Paper versus Textile	Textile dominates	5%	5%	5%
Paper versus Wood	Paper dominates	NA	10%	10%
Textile versus Wood	Textile dominates	1%	1%	1%

Table A10 continued...

iii) Water pollution sub-industry comparisons in 2005				
Industry comparisons	Dominance Outcome	SD1	SD2	SD3
Chemical versus Clay	Chemical dominates	5%	5%	5%
Chemical versus Food	Food dominates	5%	5%	5%
Chemical versus Metal	Chemical dominates	1%	1%	1%
Chemical versus Paper	Chemical dominates	10%	10%	10%
Chemical versus Textile	NA	NA	NA	NA
Chemical versus Wood	Chemical dominates	1%	1%	1%
Clay versus Food	Food dominates	1%	1%	1%
Clay versus Metal	Clay dominates	10%	10%	10%
Clay versus Paper	NA	NA	NA	NÀ
Clay versus Textile	Textile dominates	5%	5%	5%
Clay versus Wood	NA	NA	NA	NA
Food versus Metal	Food dominates	1%	1%	1%
Food versus Paper	Food dominates	1%	1%	1%
Food versus Textile	Food dominates	10%	10%	10%
Food versus Wood	Food dominates	1%	1%	1%
Metal versus Paper	Paper dominates	10%	10%	10%
Metal versus Textile	Textile dominates	1%	1%	1%
Metal versus Wood	NA			
Paper versus Textile	Textile dominates	10%	10%	10%
Paper versus Wood	Paper dominates	10%	10%	10%
Textile versus Wood	Textile dominates	1%	1%	1%