The Maple Leaf in the OECD

CANADA'S ENVIRONMENTAL PERFORMANCE

David Suzuki Foundation

SOLUTIONS ARE IN OUR NATURE

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INTRODUCTION

Along with other nations, Canada has committed to achieving a more environmentally sustainable future by signing agreements at international forums, including the 1992 United Nations Conference on Environment and Development (UNCED) and the World Summit on Sustainable Development in 2002. A key question is how successful has Canada been in meeting these international commitments to achieve sustainability?

A pioneering evaluation of Canada's progress in achieving environmental sustainability by David Boyd (2001) found that Canada's record was among the worst of developed countries, ranking 28th out of 29. In response, David Suzuki Foundation (DSF) published a comprehensive plan to show how Canada could achieve sustainability within a generation (Boyd 2004). As part of this plan, DSF asked a research team at Simon Fraser University to track Canada's environmental record on an ongoing basis. The first evaluation report published by the SFU research team in 2005 showed that Canada's environmental record was poor compared to other developed countries (Gunton et al. 2005). **Canada ranked 28th out of 30 countries**.

This report is the second evaluation completed by the Simon Fraser research team. This study uses 28 environmental indicators to assess Canada's environmental performance. The findings of this report show that Canada continues to perform poorly compared to other countries. **Canada ranks 24th out of 25 countries**.

This report also extends the research in previous reports by analysing the reasons for Canada's poor environmental performance. The findings show that Canada's poor record is not due to natural factors such as climate and geography. Instead, Canada's lacklustre record is due to poor environmental policies. **If Canadian environmental policies were comparable to the top three OECD countries, Canada's environmental rank would move from 24th to 1st in the OECD.**

This finding is good news for Canadians because it shows that our poor record is caused by public policy factors that we can control; rather than factors that we can not control, such as climate and geography. Canada has the capacity to improve dramatically its environmental performance and become a world leader in sustainability if it strengthens its environmental policies. In this report, we will document Canada's environmental record, assess the reasons for Canada's performance, and identify the policy changes required to make Canada a world leader. We begin with a discussion of our methodology.

METHODOLOGY AND APPROACH

Our methodology for assessing Canada's environmental performance has been developed over the past four years. The first step in our research was a review of existing approaches for evaluating environmental performance. Over ten approaches were examined. Based on the review, the pressure-state-response model and environmental indicator system developed by the Organization of Economic Cooperation and Development (OECD) were selected as the foundation for our evaluation system (OECD 2005). The OECD approach was selected because it is the most comprehensive system currently available. The OECD system includes: environmental indicators, environmental data, and composite index methods for comparative analysis (e.g., OECD 2005, Nardo et al. 2005). Further, the OECD environmental reporting system is adopted by the OECD-member countries and has been tested and refined over several decades of experience. Consequently, the OECD environmental evaluation system has greater credibility among OECD countries than other approaches.

We selected 28 environmental indicators that assess different aspects of environmental performance from the OECD environmental monitoring system. Unless otherwise stated, data for the indicators are provided from the OECD environmental data compendium (OECD 2009). The OECD data set is used because of the due diligence review undertaken by the OECD to enhance reliability and comparability of data. The only instances where non-OECD environmental data are used are if OECD data are not available. To ensure that environmental data can be compared among countries, the indicators use scale adjustments such as per capita, per unit of land, or per unit of economic output to adjust for differences in country size and wealth. The list of environmental indicators and the units of measurement are provided in tables 3 through 8. The year of the data reported in the most recent 2009 OECD environmental data compendium is predominantly for the years 2005 and 2006.

The next step is to interpret the environmental data to assess environmental performance. The method we use for assessing environmental performance is a cross-sectional comparison that measures or "benchmarks" Canada's performance against other jurisdictions. The cross-sectional method has several strengths. First, the data for cross-sectional comparisons are available. Second, benchmarks set by the best performing countries provide feasible environmental goals for Canada: if other countries are achieving a certain level of environmental performance, Canada could as well. Cross-sectional comparisons between Canada and other countries are shown in the following two ways.

- **Environmental Performance Rank (EPR**), defined as Canada's ordinal rank relative to other OECD countries.
- **Environmental Performance Grade (EPG)**, defined as Canada's performance relative to the best and worst performing OECD countries.

The EPR and the EPG are calculated for each of the 28 environmental indicators. The indicators are also used to calculate an overall EPR and EPG for each country by converting all the indicators to an index value, summing the indicators to calculate the composite indicator value, and then ranking each country from best to worst.

The methodology we use in this study incorporates some changes from our previous 2005 study. First, there is a slight change in the environmental indicators we use. Two OECD indicators used in our previous study were dropped: per capita fisheries capture and fisheries capture as a percent of world catch. We concluded that these two indicators are heavily influenced by countries access to water and therefore do not provide a good indication of a country’s sustainable fishing practices. We are examining potential alternative fisheries indicators for future studies. We have also added a second indicator for protected areas. Both our 2005 study and this study use the indicator for protected areas based on all IUCN categories (1-6). This study adds the second indicator for protected areas based on the more restricted IUCN categories (1-3) that provide better conservation of ecological values. This change is made to better capture the wide divergence in levels of protection in the 6 IUCN categories.

A second change is that the overall composite ratings for countries are calculated differently. In the 2005 study, we calculated the composite rank for a country by averaging the ordinal ranks for all of the environmental indicators and then ranking the countries based on their average ordinal rank. In this study, we calculate the composite rank by converting all environmental indicators to an index, summing the index, and ranking the countries based on their summed index value. The difference with the method that we use in this study compared to our 2005 study is that this index method better captures the differences in relative performance for each indicator in calculating the overall country ranks.

A third change is that in the 2005 study we used all 30 OECD countries in our analysis. The problem with using all 30 OECD countries is some countries are not good benchmarks for each other because of widely divergent levels of economic output per capita. Using Turkey, for example, as a benchmark for Canada is not particularly useful because Turkey’s environmental performance is driven by low levels of economic consumption, which Canada would not want to replicate. More appropriate benchmarks for Canada are countries with similar standards of living. Consequently, only OECD countries with per capita incomes within 50% of Canada’s were included. This criterion reduced the number of OECD countries used in the comparison from 30 to the 25 countries listed in table 1. The following five countries were dropped from the analysis: Turkey, Mexico, Poland, Slovak Republic, and Hungary.

A final change in this study compared to our 2005 study is that this study includes a comprehensive analysis of the reasons for differences in the environmental performance of OECD countries. The methodology and findings regarding reasons for differences in environmental performance are discussed later in this report.

Several limitations should be kept in mind when interpreting the comparative findings on environmental performance. First, a high ranking performance on an environmental indicator does not necessarily mean satisfactory performance. The best performing countries may **not** be achieving sustainable levels of environmental performance. This circumstance is certainly true for indicators such as greenhouse gas emissions where it is widely accepted that major reductions are required by all countries to mitigate climate change. The best way of overcoming this limitation is to compare environmental performance against a sustainability objective or target. However, we are unable to do this because widely accepted sustainability objectives are not available for most indicators. Hopefully, in future years environmental objectives will be available as a basis for assessing environmental performance.

A second limitation is that the quality of data varies from country to country despite the due diligence efforts of the OECD. Species at risk data, for example, may not accurately indicate the number of species at risk because the data are limited to the number of species assessed by each country. Many species at risk may not be listed simply because they have not yet been assessed. A third limitation is that although the environmental indicators developed by the OECD are designed to measure environmental performance, the OECD indicators do not fully capture important differences in environmental impacts. For example, the indicator used for pesticides measures the total quantity of pesticides used per unit of arable land but does not capture the variation in environmental impact associated with the toxicity of different pesticides used. Consequently, although the OECD environmental indicators provide good overall indication of environmental performance, individual indicator results should be interpreted with caution. We provide specific qualifications for each indicator in the following discussion of results.

FINDINGS

Environmental Rank by Country

The overall environmental ranks for the 25 OECD countries we reviewed are shown in table 1. The top five countries in order of rank are Denmark, Sweden, Norway, Switzerland, and Germany. Canada ranks 24th and the United States ranks last. The ranking results for 1992 show that most countries' ranks have not changed significantly over the last 16 years. Denmark, Sweden, and Norway have remained the top ranked countries while Canada and the United States have remained the lowest ranked countries. It is interesting to note that two countries show a significant improvement in their ranks: Germany which has moved from 18th to 5th and the Netherlands which has moved from 20th to 7th.

Table 1: Overall country ranks

COUNTRY	1992	2002	CURRENT STUDY
Denmark	1	1	1
Sweden	2	5	2
Norway	3	7	3
Switzerland	6	3	4
Germany	18	4	5
Austria	9	2	6
Netherlands	20	6	7
Italy	12	9	8
United Kingdom	14	13	9
Finland	8	8	10
New Zealand	7	16	11
Korea	10	12	12
Spain	4	17	13
Japan	15	18	14
Greece	5	14	15
France	13	10	16
Ireland	16	19	17
Czech Republic	19	15	18
Portugal	11	11	19
Australia	17	23	20
Luxembourg	23	21	21
Iceland	21	20	22
Belgium	22	22	23
Canada	**24**	**24**	**24**
United States	25	25	25

Environmental Rank by Indicator

To better understand Canada's overall environmental performance it is important to go beyond the overall country ranks and examine Canada's performance by indicator to determine areas of strength and weakness. For easy reference, we summarize Canada's rank and grade by indicator in table 2. We then provide a more detailed review of Canada's performance by indicators grouped under thematic headings based on sustainability goals developed by the David Suzuki Foundation (Boyd 2004). The rank shows Canada's position relative to the other 24 OECD countries. The grade measures Canada's performance using an index value calculated on a scale between 0 and 100 based on the difference between the best and worst performing OECD countries. The index value is converted to a letter grade based on the standard scale for converting numerical grades to letter grades used in Canadian universities. The **absolute trend** shows whether Canada's performance is improving or deteriorating from 1992 to the present. The **relative trend** shows whether Canada's performance is improving or deteriorating at a faster rate than the OECD average. A positive sign (+**)** indicates an improvement and a negative sign (**–)** indicates deterioration in Canada's performance. The top three ranked countries for each indicator are also provided for reference. Analysis of the policies of the top performing countries can provide a guide for how lower performing countries can improve.

Efficiency and Clean Energy

Energy Consumption: Energy consumption correlates strongly with a large number of environmental impacts, and is therefore an important indicator of a country's environmental performance. Energy consumption is measured in millions of tonnes of oil equivalent (toe) per capita. Canada's energy consumption is among the highest rates in the OECD, ranked 23rd. Canada's rate of energy consumption of 6.3 toe per capita is 66% higher than the OECD average. The trends in energy consumption for Canada are mixed: energy consumption has been increasing but at a slightly slower rate than the OECD average increase.

Energy Intensity: Differences in energy consumption per capita can, in part, be due to differences in per capita income. Energy intensity controls for this difference by measuring the amount of energy consumed per unit of gross domestic product (GDP). Canada's rank in energy intensity (24th) is even worse than energy consumption. Canada's energy intensity is almost double the OECD average. This result shows that per capita income is not the reason for Canada's high energy consumption. Instead, Canada simply uses more energy per dollar of production than other countries. On a positive note, Canada's energy intensity is declining. However, it is declining at a slower rate than the OECD average.

Table 2: Canada's rank by environmental indicator

INDICATOR	RANK	GRADE
Carbon Monoxide (kg./cap.)	25	F
Nuclear Waste (kg./cap.)	25	F
Volatile Organic Compounds (kg./cap.)	25	F
Energy Intensity (toe/$ of GDP)	24	F
Environmental Pricing (% of GDP)	24	F
Sulphur Oxides (kg./cap.)	24	F
Energy Consumption (toe/cap.)	23	F
Nitrogen Oxides (kg./cap.)	23	F
Vehicular Use (vehicle km./cap.)	23	F
Greenhouse Gases (tonnes/cap.)	22	F
Water Consumption (cu. m./cap.)	22	F
Renewable Energy without Hydro (% of production)	19	F
Protected Areas (class1-6 as % of land area)	17	F
Number of Species at Risk	16	B
Official Development Assistance (% of GNI)	14	F
Recycling Municipal Waste (%)	10	D
Timber Harvest to Timber Growth Ratio	9	C
Pollution Abatement and Control Expenditure (% of GDP)	8	C
Proportion of Species at Risk	8	C
Sewage Treatment (%)	8	B
Ozone Depleting Substances (kg./cap.)	7 of 10	A
Protected Areas (class 1-3 as % of land area)	6	F
Pesticide Use (kg./sq. km. arable land)	6	A
Renewable Energy with Hydro (% of production)	5	D
Municipal Waste (kg./cap.)	5	B
Livestock Intensity (livestock units/ sq. km. arable land)	5	A
Timber Harvest (cu. m./sq. km. forestland)	5	A
Fertilizer Use (tonnes/ sq. km. arable land)	3	A

Renewable Energy: Generating a higher proportion of energy from renewable energy sources can mitigate environmental impacts significantly. With its plentiful supply of hydro power, Canada generates a high proportion of its electricity from renewable sources (60%) and ranks 5th among OECD countries. Canada's trend is negative, showing a small decline in the proportion of electricity derived from renewable sources while the average of the OECD shows a small increase.

Renewable Energy without Hydro: Although hydropower is renewable, it can have a higher environmental impact than other forms of renewable energy such as wind, solar, tidal, and geothermal. Impacts of hydro can include flooding, vegetation decay causing greenhouse gas emissions, and major disruptions of watershed ecological systems. Consequently, we also measure renewable sources as a proportion of electricity consumption without including hydro. Canada generates only 1.9% of its electricity from non-hydro renewable sources, ranking 19th among OECD countries. The trend is positive, with Canada registering an increase in proportion of electricity from non-hydro renewable energy sources, albeit from a small base. Canada's rate of increase is however slower than the average increase for OECD countries.

Distance Travelled: An important variable in efficiency and energy consumption is reliance on private vehicles for transportation. Vehicular use generates significant environmental impacts. The OECD uses private vehicle-km. per capita to assess the pressure placed by vehicles on the environment. Canada ranks 23rd in vehicle use, tied with Australia. The trend in vehicle use is negative, increasing by 18% since 1992, a slightly lower rate of increase than the OECD average of 22%.

Table 3: Efficiency and Clean Energy indicators

INDICATOR	RANK	GRADE	BEST PERFORMERS	ABSOLUTE TREND	RELATIVE TREND
Energy Consumption (toe/cap.)	23	F	1st - Greece 2nd - Portugal 3rd - Spain	-	+
Energy Intensity (toe/$ of GDP)	24	F	1st - Greece 2nd - Ireland 3rd - Switzerland	+	-
Renewable Energy with Hydro (% of production)	5	D	1st - Iceland 2nd - Norway 3rd - Austria	-	-
Renewable Energy without Hydro (% of production)	19	F	1st - Iceland 2nd - Denmark 3rd - Finland	+	-
Vehicular Use (vehicle km./cap.)	23	F	1st - Korea 2nd - Czech Republic 3rd - Spain	-	+

Waste and Pollution

Greenhouse Gas Emissions: Greenhouse gases (GHGs) include a number of specific gases the most important of which are carbon dioxide, methane, and nitrous oxide. The primary sources of GHG emissions are energy consumption in transportation (27%), fossil fuel production and distribution (17%), and electricity and heat generation (17%). The remaining 39% of GHG emissions in Canada come primarily from agriculture and manufacturing (Canada, Environment Canada 2008). Canada is one of the worst emitters of GHGs, ranked 22nd among OECD countries. Canada's per capita emissions are 67% higher than the OECD average. **Emissions have increased in absolute terms by 26.2% between 1990 and 2007, despite Canada's binding commitment under the Kyoto Protocol to reduce emissions by 6% from**

1990 levels by 2008-2012. On a per capita basis, Canada's emissions have increased while the average per capita emissions in OECD countries have declined.

Sulphur Oxides: Sulphur oxides are emitted from mining smelters, electrical power plants, pulp mills, and the oil and gas sector. Sulphur oxides impact human health, causing asthma, coughing, and chest pain. Sulphur oxides also create acid rain, which seriously harms aquatic and terrestrial ecosystems by altering the acidity of the environment. Canada emits 64 kg/capita of sulphur oxides, more than three times higher than the OECD average. Canada ranks among the worst emitters at 24th, exceeded by only one other country: Australia. Canada has been successful in reducing its sulphur oxides emissions by 42% from 1992 to 2008. However, Canada's rate of decrease is below the OECD average decrease of 50%. Also, recent research indicates that the environment is more sensitive to acid rain than previously thought and that a more dramatic decrease in the range of 75% is required to protect the environment (OECD 2004: 39).

Nitrogen Oxides: Nitrogen oxides are created by the combustion of fossil fuels. Like sulphur oxides, nitrogen oxides cause harm to human health as well as the aquatic and terrestrial environment. Canada's rate of nitrogen oxides emissions rank 23rd and are more than double the OECD average. Canada has reduced its emissions by 17% from 1992 levels, but the rate of reduction is below the OECD average decrease of 25%.

Volatile Organic Compounds: Volatile organic compounds (VOCs) come from vehicle emissions, chemical manufacturing, and evaporation of petroleum-based products. VOCs combine with nitrogen oxides to form smog and ground-level ozone, which impacts human health and growth of fauna. Canada has the worst per capita emissions of VOCs in the OECD, ranked 25th. VOC emissions have been reduced by 27% since 1992, but the reduction is well below the OECD average reduction of 40%.

Carbon Monoxide: Carbon monoxide is produced by the combustion of fossil fuels, mainly by vehicles. Carbon monoxide imposes a health risk by impairing the ability of lungs to absorb oxygen. Canada has the highest per capita carbon monoxide emissions in the OECD; these emissions are more than three times the OECD average. Although Canada's carbon monoxide emissions have been reduced by 32% since 1992, this reduction is below the OECD average of 45%.

Ozone Depleting Substances: Ozone depleting substances (ODSs) are used in refrigeration, fire extinguishers, plastics, and pesticides. ODSs damage the earth's ozone layer, leading to increased penetration of ultraviolet radiation that impacts human health and ecosystems. Through various international agreements, the use of ODSs is being phased out, with a full phasing out planned for 2020. ODSs data are limited to only ten OECD countries. Canada ranks 7th out of the 10 countries. ODSs emissions have been reduced by 95% since 1992, a slightly better rate of reduction that the OECD average of 91%.

Nuclear Waste: Nuclear energy accounts for about 16% of Canadian electricity production, located in the three provinces of Ontario, Quebec, and New Brunswick. Nuclear waste is generated by nuclear energy plants in these three provinces and uranium mining. Nuclear waste remains radioactive for over 250,000 years, thus posing a long-term and serious risk to the environment. Canada is the largest generator of nuclear wastes in the OECD, with a per capita rate over seven times the OECD average. Canada has reduced its rate of waste generation by 12% since 1992, slightly higher than the OECD average reduction of 9%.

Municipal Waste: Municipal waste is defined as waste from households and commercial establishments, but excludes industrial wastes. Disposal of municipal waste by landfills and incineration generates harmful pollutants that can contaminate air and water. Canada has a relatively good record on municipal waste, ranking 5th among the 25 OECD countries. Canada's generation of municipal waste is about one-quarter below the OECD average. Canada has reduced per capita municipal waste by 37% since 1992.

Recycling of Municipal Waste: Municipal waste recycling involves the reuse of municipal waste in a production process other than fuel that diverts it from the waste stream. Canada ranks 10th in the percentage of municipal waste recycled. The percentage of waste recycled has increased from 18.1% in 1992 to 26.8% in 2006. However, the rate of increase in recycling is well below the average increase for OECD countries.

Environmental Pricing: An important means of environment protection is to charge a price for activities that harm the environment. Carbon taxes that charge a price for greenhouse gas emissions, for example, encourage emission reduction. It is important to note that so called "green taxes" need not involve any increase in the overall tax burden. Revenue from green taxes can be used to reduce other taxes with no net revenue gain. The tax system simply becomes more efficient by increasing taxes on polluting activities and reducing taxes on non-polluting activities. To assess the role of environmental pricing, the OECD estimates the total revenue collected from environmental related taxes. Environmental related taxes are defined by the OECD (2005: 286) as "any compulsory, unrequited payment to general government levied in tax bases deemed to be of particular environmental relevance." Canada ranks near the bottom (24th) in environmental taxes as a percentage of GDP. The trend is negative. Environmental taxes have declined since 1995 from 1.7% to 1.2% of GDP. Canada's level of environmental taxes is one-quarter the level of Demark, which, at 4.8%, has the highest level of environmental taxes and the best environmental rating among OECD countries.

Pollution Abatement and Control Expenditures: Pollution abatement and control expenditures (PACE) help measure the effort that a country makes to reduce environmental damage. PACE are defined by the OECD (2005: 280) as "purposeful activities aimed at the prevention, reduction and elimination of pollution or nuisances that could have a harmful effect on the environment." Canada's PACE are 1.2% of GDP, slightly above the OECD average of

1.0%, giving Canada a rank of 8th. Canada's trends in PACE are positive; PACE have increased since 2002 while average PACE have declined among OECD countries.

Table 4: Waste and Pollution indicators

INDICATOR	RANK	GRADE	BEST PERFORMERS	ABSOLUTE TREND	RELATIVE TREND
Greenhouse Gases (tonnes/cap.)	22	F	1st - Switzerland 2nd - Sweden 3rd - Portugal	-	-
Sulphur Oxides (kg./cap.)	24	F	1st - Switzerland 2nd - Austria 3rd - Netherlands	+	-
Nitrogen Oxides (kg./cap.)	23	F	1st - Switzerland 2nd - Japan 3rd - Germany	+	-
Volatile Organic Compounds (kg./cap.)	25	F	1st - Belgium 2nd - Netherlands 3rd - Japan	+	-
Carbon Monoxide (kg./cap.)	25	F	1st - Korea 2nd - Japan 3rd - Netherlands	+	-
Ozone Depleting Substances (kg./cap.)	7 of 10	A	1st - Switzerland 2nd - Norway 3rd - Iceland	+	+
Nuclear Waste (kg./cap.)	25	F	1st - Australia 1st - New Zealand 1st - Austria *	+	+
Municipal Waste (kg./cap.)	5	B	1st - Czech Republic 2nd - New Zealand 3rd - Korea	+	+
Recycling Municipal Waste (%)	10	D	1st - Korea 2nd - Sweden 3rd - Switzerland	+	-
Pollution Abatement and Control Expenditures (% of GDP)	8	C	1st - Germany 1st - Netherlands ** 3rd - Denmark	+	+
Environmental Pricing (% of GDP)	24	F	1st - Denmark 2nd - Netherlands 3rd - Finland	-	-

* Australia, New Zealand, Austria, Denmark, Greece, Iceland, Ireland, Italy, Luxembourg, Norway, and Portugal all generate no nuclear waste because they do not utilize nuclear energy.

** Germany and Netherlands expend equivalent proportions of GGD so both place first.

Protecting and Conserving Water

Water Consumption: Water consumption is defined by the OECD as net water withdrawals from source, with net being measured by the difference between water withdrawn and water returned to the source. Water used for hydroelectric generation therefore would not be defined as water consumption. Canada's water consumption of 1,590 cubic metres/capita is second highest in the OECD, exceeded by only the United States and is more than double the OECD average. The trends in water consumption are positive: Canada's rate of consumption declined 8.3% since 1992 and has declined at a slightly faster rate than the OECD average of 6.7%.

Sewage Treatment: A major cause of water pollution is the release of untreated sewage into water bodies. Untreated sewage can result in increased nutrient levels that can cause eutrophication and toxic algae blooms that harm aquatic systems as well as high levels of disease causing pathogens from human sewage. The impact of sewage on water quality can be reduced by sewage treatment, normally divided into three levels: primary, which uses filters and screens to remove solids and organic matter; secondary, which reduces bacteria by various biological processes; and tertiary, which removes additional nutrients and toxic components. Currently, 89% of Canadian sewage is treated, slightly above the OECD average of 80%. Canada's rate of sewage treatment ranks 8th among OECD countries. The trend in Canada's rate of sewage treatment is positive: the proportion of sewage being treated increased significantly from 63% in 1992, and increased at a faster rate than the OECD average.

Table 5: Protecting and Conserving Water indicators

INDICATOR	RANK	GRADE	BEST PERFORMERS	ABSOLUTE TREND	RELATIVE TREND
Water Consumption (cu. m./cap.)	22	F	1st - Denmark 2nd - Luxembourg 3rd - Czech Republic	+	+
Sewage Treatment (%)	8	B	1st - Netherlands 2nd - U. K. 3rd - Switzerland	+	+

Producing Healthy Food

Pesticide Use: Pesticides are a major source of environmental contamination linked with serious human health impacts including cancer and various neurological disorders such as Parkinson's Disease (Boyd 2006). Pesticide contamination is widespread, with some studies documenting the presence of pesticides contamination in 100% of study participants (Environment Defence Fund 2005, 2006). Reducing pesticide use and reducing the toxicity of pesticides in use are important measures to improve environmental health. Canada's pesticide use is measured in kilograms of pesticide used per square km. of arable land. Canada has a relatively low level of pesticide use based on this indicator, ranked 6th among OECD countries and about one-fifth the OECD average rate of pesticide use. The trend in Canada's pesticide use is negative: Canada's rate of pesticide use increased slightly since 1992 (7%), while the average rate of pesticide use in OECD countries declined significantly by 35% since 1992. Of greater concern than the rate of pesticide use, is the toxicity of pesticides used. There are no good data on the quantity of types of pesticide used based on toxicity by country. However, one recent study documents several major concerns in Canadian standards. Currently, 60 active ingredients in pesticides used in Canada are banned in other OECD countries for environmental health reasons. Further, the standards in Canada for the maximum residue limits on the amount of pesticide present in food are significantly weaker than other OECD countries (Boyd 2006). Therefore, although Canada's overall rate of pesticide use is lower than many other OECD countries, the environmental impacts may be higher due to the higher toxicity of pesticides used.

Fertilizer Use: Fertilizers are a major source of nutrient contamination that can damage aquatic systems by increase nitrogen and phosphorous levels. Fertilizer use also contributes to climate change by generating nitrous oxides emissions from soil. In 2007, nitrous oxide emissions accounted for 4% of Canada's greenhouse gas emissions (Canada, Environment Canada 2008). The rate of fertilizer use is measured by tonnes per square km. of arable land. Canada's rate of fertilizer use is relatively low, ranked 3rd among OECD countries. Canada's rate of fertilizer use is only one-fifth the average for the OECD. The trend in fertilizer use in Canada is negative: the rate of use increased 35% since 1992, and increased at a much faster rate than the OECD average increase of 7%.

Livestock Intensity: Livestock have a number of environmental impacts including contamination of water from manure and contamination of air by release of greenhouse gases. In 2007, the release of methane gas from livestock contributed about 4% of Canada's GHG emissions (Canada, Environment Canada 2008). Livestock grazing also negatively impacts natural habitats. Livestock intensity is measured by a standardized animal unit equivalent for cattle, sheep, goats, pigs, horses, and mules per square km. of arable land and grassland. Canada's livestock intensity is relatively low among OECD countries, ranked 5th and about one-third the average for the OECD. Canada's trend line in livestock intensity is negative: livestock intensity increased by 10% since 1992, while it decreased by an average 3.5% among OECD countries.

Table 6: Producing Healthy Food indicators

INDICATOR	RANK	GRADE	BEST PERFORMERS	ABSOLUTE TREND	RELATIVE TREND
Pesticide Use (kg./sq. km· arable land)	6	A	1st - Iceland 2nd - Australia 3rd - Finland	-	-
Fertilizer Use (tonnes/sq. km. arable land)	3	A	1st - Australia 2nd - Denmark 3rd - Canada	-	-
Livestock Intensity (livestock units/sq.km. arable land)	5	A	1st - Iceland 2nd - Australia 3rd - Greece	-	-

Conserving and Protecting Nature

Species at Risk: A useful indicator of ecological health is species at risk of becoming extinct in the wild. Species at risk are determined by scientific committees based on studies of individual species. In Canada, assessments are made by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC). Two indicators of species at risk are used: the number of species at risk and the proportion of species at risk. Species assessed include terrestrial and aquatic species and flora and fauna. Canada ranks 16th in the number of species at risk and 8th in the proportion of species at risk. Canada's trend in species at risk is negative. Since 1992, the number of species at risk increased by 45%, higher than the OECD average increase of 27%. Since 1992, the proportion of species at risk in Canada increased by three times from 4.8% to 16.0%, while the OECD average remained relatively constant, increasing from 20.2% to 21.8%. However, an important qualification should be kept in mind when interpreting species at risk data. The number of species at risk depends on the number of species assessed. In Canada, the number of species assessed increased from 1,685 in 2000 to 7,732 in 2005 (Canada, Environment Canada 2009). This is still a small proportion of the estimated 137,500 species in Canada (OECD 2004: 76); therefore, the number of species at risk may be much higher. Trends are also difficult to assess because they are influenced by the change in the number of species assessed. One way of controlling for this bias is a comparison of assessments of the same species over time. Results from the period 1985 to 2004 based on 205 species show that 31% of the species were placed in a higher risk category and 7% in a lower risk category (Canada, Treasury Board 2004). A more recent study based on 1,330 species shows that 39% were moved to a higher risk category and 31% to a lower risk category (Canada, Environment Canada 2009). These results may indicate a negative trend in species health.

Protected Areas: Protected areas are areas of land or water with restrictions on activities that damage ecological, natural, recreational, and/or cultural features. The proportion of the land base that is designated as protected is an important indicator of efforts to protect the environment. The level of restrictions on activities determines the extent of protection. The World Conservation Union (IUCN) classifies protection under six categories according to management goals. IUCN categories 1-3 provide the highest levels of protection by restricting all activities that may damage conservation, wilderness, and/or ecological objectives. Categories 4-6 have lower levels of protection and allow a wider range of uses including sustainable resource extraction. To reflect this significant difference in the level of protection, two indicators are used for protected areas: the proportion of the land base in categories 1-3 and the proportion of the land base in categories 1-6. Canada ranks 6th in the proportion of the land base in categories 1-3 and 17th in the proportion of the land base in categories 1-6. The trends in protected areas can not be accurately assessed do to changing definitions. A common goal for protected areas recommended in the Brundtland Commission (WCED 1987) is to protect 12% of the land base. Protected areas in Canada represent 6.7% of the land base, which is well below the 12% objective. Further, almost one-quarter (10 of 39) of terrestrial regions in Canada have no protected designation and most aquatic regions remain unprotected (OECD 2004: 83).

Forest Management: Forests cover 45% of Canada's land base and provide habitat for two-thirds of Canada's wildlife (OECD 2004: 85). Management of the forest base is therefore an important environmental objective. Protected area designation is a significant tool for managing forests. About 6.8% of Canada's forests are protected (OECD 2004: 85). Two indicators that are used to assess forest management practices are the timber harvest intensity measured by the volume of timber harvested per sq. km. of forested land and the volume of timber harvested relative to its growth. A harvest-to-growth ratio of under one indicates that forests are being harvested at a slower rate than regeneration and the volume of forests is therefore increasing. A ratio greater than one indicates that the volume of forests is declining. Canada ranks relatively high on forest management among OECD countries: 5th in timber harvest intensity and 9th in the timber-harvest-to-growth ratio. The trends in timber harvest intensity are negative and the trends in timber harvest to growth are positive. However, several cautions should be noted when interpreting these indicators. First, the impact of forest harvesting will vary with the way harvesting is done. Clear cutting and harvesting in more environmentally sensitive areas, for example, have more damaging environmental impacts. Ratios may also change significantly from year to year depending on economic and other conditions. Therefore, these indicators of forest management should be considered as only very rough measures of the quality of management.

Table 7: Conserving and Protecting Nature indicators

INDICATOR	RANK	GRADE	BEST PERFORMERS	ABSOLUTE TREND	RELATIVE TREND
Number of Species at Risk	16	B	1st - Iceland 2nd - Ireland 3rd - Finland	-	-
Proportion of Species at Risk	8	C	1st - Australia 2nd - Ireland 3rd - Korea	-	-
Protected Areas (class 1-6 as % of land area)	17	F	1st - Germany 2nd - Switzerland 3rd - Austria	n.a	n.a.
Protected Areas (class 1-3 as % of land area)	6	F	1st - New Zealand 2nd - Netherlands 3rd - Sweden	n.a.	n.a
Timber Harvest (cu. m./sq. km. forestland)	5	A	1st - Greece 2nd - Australia 3rd - Italy	-	-
Timber Harvest to Timber Growth Ratio	9	C	1st - Korea 2nd - Japan 3rd - Italy	+	+

n.a. = not available

Promoting Global Sustainability

Official Development Assistance: A means of promoting global sustainability is to provide support for sustainable development in other nations. A common indicator of global support is official development assistance measured as a proportion of the donor country's gross national income (GNI). An important qualification in using this indicator is that the environmental effect will vary depending on how the assistance is used. Unfortunately, there is no available indicator that measures environmental benefits of expenditures in a comparable way. A widely accepted objective for developed countries is to contribute at least 0.7% of GNI (UN 2002). Canada's official development assistance is 0.34%, less than one-half of the international objective and less than the OECD average of 0.43%. Overall, Canada ranks 14th in official development assistance and the trends are negative: Canada's assistance has declined since 1992 from 0.46% to 0.34%, while the OECD average remained constant.

Table 8: Promoting Global Sustainability indicator

INDICATOR	RANK	GRADE	BEST PERFORMERS	ABSOLUTE TREND	RELATIVE TREND
Official Development Assistance (% of GNI)	14	F	1st - Norway 1st - Sweden * 3rd - Luxembourg	-	-

* Norway and Sweden contribute equivalent proportions of GNI so both place first.

FACTORS INFLUENCING ENVIRONMENTAL PERFORMANCE

Introduction

The previous section of the report shows that Canada's environmental record is among the worst of OECD countries. An obvious and important question comes to mind: why is Canada's record so poor compared to other developed countries and what can be done to improve Canada's performance? To address this question, we completed an analysis of factors that explain environmental performance.

Methodology

Our methodology for assessing factors explaining a country's performance consists of the following steps. First, we reviewed the literature to identify factors that may affect a country's environmental performance. Based on this review we identified seven factors listed in table 9.

The next step was to estimate the role of these factors by statistical analysis of the relationship between the factors and environmental performance. Appendix A provides details of the statistical methodology used, while Appendix B provides detailed statistics from software output. In brief, we developed numeric indicators for each of the seven factors potentially affecting environmental performance. Next, we collected data for the 25 OECD countries for each of the seven factor indicators and assessed the role of each in explaining the differences in environmental performance. We examined the role of these factors in explaining environmental performance for both overall performance defined by the environmental index for each country and by three subcategories of environmental performance: energy efficiency, waste and pollution, and GHG emissions. We selected these three subcategories for more detailed analysis because they are the areas where Canada's performance most significantly lags other OECD countries.

Findings

The results of our statistical analysis are summarized in table 10. The results show that only two of the seven factors—energy prices and environmental governance—explain differences in the overall environmental performance index (Composite Environmental Index) among OECD countries. Together, energy prices and environmental governance explain 42% of the variation. Both factors are roughly equally important to explaining the variation. For energy efficiency, two factors explain 68% of the variation among OECD countries: energy prices explain 39% and climate explains 29%. For the waste and pollution indicators, two factors explain 53% of the variation: energy prices (45%) and environmental governance (9%). For GHG emissions, six factors explain 94% of the variation, with energy prices accounting for 70% of the variation, followed by population growth (9%), economic output (9%), environmental governance (3%), climate (2%), and industrial structure (2%).

Table 9: Influential factor descriptions and numeric indicators

FACTOR	HYPOTHESIS	INDICATOR
Climate [a]	Extreme temperatures increase energy consumption for space heating and cooling. Temperature regimes may also affect sustainable production of food, natural resource conservation, and biodiversity.	Total heating and cooling degree days. A 'degree day' is a measure of the average temperature's departure from a human comfort level of 18 °C (65 °F). To capture the effects of both, the climate metric sums heating and cooling degree days to find total degree days.
Population Growth [b]	Growing populations increase consumption of ecosystems and their corresponding services, as well as strain ecosystem assimilative capacity.	Annual percentage increase in a country's population from 2001 to 2002.
Economic Output [c]	Environmental performance decreases as level of affluence increases consumption of resources.	GDP per capita for 2002.
Technological Development [d]	New technologies use resources more efficiently or allow substitution with less damaging processes or materials.	Value from 0 to 1 based on the UN's Technology Achievement Index for 2002.
Industrial Structure [e]	Environmental performance decreases as an economy becomes more industrialised, and, thus more energy intensive with a heavier pollution load.	Gross value added to an economy from three most energy-intensive sectors (transport sector, non-metallic minerals, and refined petroleum products, chemicals and rubber) as proportion of GDP for 2002.
Energy Prices [f]	Higher energy prices promote conservation, efficiency, and innovation.	Consumption-based weighted average of gasoline, diesel, natural gas, and electricity prices (both residential and industrial) per toe for 2002.
Environmental Governance [g]	Effective governance of a variety of pollutants and environmental issues increases environmental sustainability.	Dimensionless value representing aspects of environmental governance based on responses to questions 11.01 to 11.11 from the Executive Opinion Survey. The analysis uses the sum of survey question scores across the 11 governance areas.

a – data source: World Resources Institute Climate Analysis Indicators Tool Excel v. 3.0
b – data source: OECD Environmental Data Compendium 2004
c – data source: OECD Environmental Data Compendium 2004
d – data source: UN Human Development Report
e – data source: Energy Balances of OECD Countries 2001 – 2002, Energy Statistics of OECD Countries 2002 – 2003, National Accounts of OECD Countries Detailed Tables Volume II 1993-2004
f – data source: International Fuel Prices 2003, German Technical Co-operation, German Federal Ministry for Economic Co-operation and Development, International Energy Agency's Energy Prices and Taxes Quarterly Statistics 2005, Energy Statistics of OECD Countries 2002 - 2003
g – data source: World Economic Forum's The Global Competitiveness Report Executive Opinion Survey 2003 -2004

Table 10: Assessing the relationship between significant factors and subcategories and establishing the importance of each factor

SUBCATEGORY	EXPLAINED VARIATION (%)	SIGNIFICANT FACTORS	VARIATION EXPLAINED BY FACTOR (%)
Composite Environmental Index	42.0	Energy Prices	22.9
		Environmental Governance	19.1
Energy Efficiency	68.4	Energy Prices	39.4
		Climate	29.0
Waste and Pollution	53.2	Energy Prices	44.5
		Environmental Governance	8.7
GHG Emissions	93.8	Energy Prices	69.6
		Population Growth	9.3
		Economic Output	8.7
		Environmental Governance	2.7
		Climate	1.9
		Industrial Structure	1.5

The next step in our analysis is to assess why Canada's environmental performance is so poor. We answer this question by conducting a sensitivity analysis to illustrate how Canada's environmental ranking would change with changes in key factors affecting environmental performance. Two of the seven factors are changed: energy prices and environmental governance. These two factors are selected for the sensitivity analysis because they can be changed by public policy. The other five factors—climate, industrial structure, population growth, economic output, and technological change—are not used in the sensitivity analysis because they are extremely difficult to impossible to alter by public policy, and they have demonstrably much less impact on environmental performance. Several sensitivity analyses are done on energy prices and environmental governance. One sensitivity analysis sets energy prices and environmental governance in Canada to the average for OECD countries and a second sensitivity analysis sets them to the average for the top three OECD countries.

Results of the sensitivity analyses show that Canada's environmental performance changes dramatically with changes in energy prices (table 11). If energy prices equalled the OECD average, Canada's overall environmental rank moves from 24th to 12th. If energy prices equalled the average for the three OECD countries with the highest energy prices, Canada's environmental rank moves from 24th to 1st. The rank for waste and pollution and for GHG emissions also improves dramatically from 25th and 22nd to 1st. In absolute terms, GHG emissions decline by 71 % with the increase in energy prices.

Table 11: Changes in Canada's environmental rank with changes in energy prices and environmental governance

Subcategory	Canada's Actual Rank	Canada's Estimated Rank with Energy Prices at		Canada's Estimated Rank with Environmental Governance at		Canada's Estimated Rank with Energy Prices and Environmental Governance at	
		OECD Avg.	Top Three Avg.	OECD Avg.	Top Three Avg.	OECD Avg.	Top Three Avg.
Composite Environmental Index	24	12	1	24	17	14	1
Energy Efficiency	23	21	13	n.a.	n.a.	n.a.	n.a.
Waste and Pollution	25	13	1	24	23	14	1
GHG Emissions	22	6	1	23	21	7	1

n.a. = not applicable; environmental governance is not a significant factor for this subcategory.

Changing environmental governance also improves Canada's environmental rank, but not as dramatically (table 11). Because Canada's environmental governance is already close to the OECD average, setting environmental governance to the OECD average has no affect on Canada's overall rank. Setting Canada's environmental governance to the average of the top three OECD countries moves Canada's rank from 24th to 17th.

Decomposition Analysis

A second method for explaining differences in environmental performance is to break the economy into subsectors and model the impact of changing key factors on each subsector by a series of production and output functions. This methodology, referred to as decomposition analysis, is a data intensive approach that has been used to analyze differences in GHG emissions among countries. Due to the enormous data requirements and applicability of the methodology to a limited subset of environmental indicators, we decided to use our statistical analysis instead of decomposition analysis. However, we will summarize the findings of a recent decomposition analysis identifying the reasons for differences in GHG emissions among the G7 countries (Bataille et al. 2007).

The objective of the Bataille et al. study is to assess the role of what are referred to as "national circumstances" in explaining differences in GHG emissions. National circumstances are defined as characteristics of a country that have a significant impact on GHG emissions and can not be changed easily by public policy. The study identifies five national circumstance factors: climate, industrial structure, population distribution, production of fossil fuels, and availability of electricity resources that are low to nil emitters of greenhouse gases. The role of each factor in explaining differences in GHG emissions is estimated for the G7 countries. The results for Canada, summarized in table 12, show that overall these national circumstance factors explain only 10% of the difference in GHG emissions between Canada and the G7 average. The reason for this finding is that two potentially negative factors—industrial structure and geography—have little affect, and the other two negative factors that have a significant impact—climate and fossil fuel production—are largely offset by the positive impact of Canada's access to low-polluting electricity sources, predominantly hydro. The results of this study are therefore consistent with the findings of our analysis that demonstrates Canada's high levels of GHG emissions relative to other countries are not significantly affected by climate, industrial structure, or geography.

Table 12: Role of non-policy factors in explaining differences between Canada's greenhouse gas emissions and the G7 countries

	GHG EMISSIONS (t/cap)
G7 Average	9.93
Canada	23.32
NATIONAL CIRCUMSTANCE FACTORS	
Climate	+1.25
Geography	+0.17
Industrial Structure	+0.01
Fossil Fuel Production	+2.80
Low GHG Electricity	-2.80
Net Impact	**+1.37**
% of Difference between Canada and G7 due to National Circumstances	**10%**

Source: Bataille et al. (2007)

Policy Implications

Our analysis provides good news for Canadians. The results show that Canada's poor environmental performance is not due to factors beyond its control such as climate and geography. Instead, Canada's poor performance is caused by poor public policy. Indeed, a recent comprehensive evaluation of Canada's environmental policy-making process found that none of Canada's environmental policy processes met international best practices criteria (Ellis et al. 2010). The current study shows that the most significant policy error is the decision to set energy prices at among the lowest levels in the OECD and the failure to adopt the best environmental governance regime. Canada could dramatically improve environmental sustainability performance by adding a cost for the environmental damage caused by consuming energy, mainly fossil fuels, thereby increasing energy prices used in the Canadian economy. In this way, energy consumers would receive a more accurate signal for the actual cost to society of energy consumption. Specifically, Canada could greatly improve performance by implementing a carbon tax and/or a cap-and-trade system.

We acknowledge that increasing energy prices to sustainable levels is not easy. Moving Canadian energy prices to the OECD average would involve an increase of 78% and moving to the average of the top three OECD countries would involve an increase of 160%. The adjustments would take time and would involve significant challenges. However, if the changes were phased in over a long period and were implemented in a revenue neutral manner so that all increases were refunded back to consumers through tax cuts, the negative impacts would be relatively minor and would be more than justified by the enormous environmental benefits. We note that some provinces are already implementing these types of policies. Pricing energy at sustainable levels would also invigorate the burgeoning “green” economy. Alternative forms of energy, such as wind and tidal, would become more cost competitive with fossil fuels thus providing the “green” economy with an opportunity to increase market share, and the corresponding increases in employment from infrastructure construction (e.g., installation of wind turbines and associated power distribution equipment) and from manufacturing (e.g., wind turbines). An alternative approach to improve environmental performance would be for Canada to adopt stricter emission regulations based on the levels achieved in the best performing OECD countries such as Denmark, Sweden, and Norway. The technology to achieve lower emissions clearly exists and the adoption of stricter standards is likely easier to implement than energy price increases.

CONCLUSIONS

1. Canada's environmental performance is poor.
   - Canada has the second worst environmental record, ranked 24th out of 25 OECD countries.
   - Canada has a failing grade (F) on the following 15 environmental indicators.
     1. Energy Consumption
     2. Energy Intensity
     3. Water Consumption
     4. Environmental Pricing
     5. GHG Emissions
     6. Non-hydro Renewable Electricity
     7. Sulphur Oxides Emissions
     8. Nitrogen Oxides Emissions
     9. Volatile Organic Compound Emissions
     10. Carbon Monoxide Emissions
     11. Nuclear Waste
     12. Protected Areas-All Categories
     13. Protected Areas-Categories 1-3 (highly protected)
     14. Automobile Distance Travelled
     15. Official Development Assistance
   - Canada is the worst performer on three indicators (volatile organic compounds emissions, carbon monoxide emissions, and nuclear waste) and has the second worst record on another three indicators (energy intensity, environmental pricing, and sulphur oxides emissions).
   - Canada does not finish first on a single environmental indicator.
   - Canada's performance has deteriorated on one-half of the 28 indicators and its performance is worse than the OECD average on 18 of the 28 indicators.

2. Canada's poor environmental performance is not due to factors such as climate, geography, or industrial structure that are largely beyond its control. Instead, Canada's poor record is due to poor environmental policies, including the failure to adopt good policy-making and governance practices and the failure to price energy to reflect adequately pollution generated by the consumption of fossil fuel.

- **If Canadian energy prices and/or environmental regulations were set at levels similar to the OECD average Canada's environmental ranking would move from 24th to 12th in the OECD.**
- **If Canadian energy prices and/or environmental regulations were set at levels similar to the OECD average for the top three countries, Canada's environmental ranking would move from 24th to 1st in the OECD.**

Therefore, Canada could greatly improve environmental performance by implementing a mechanism or process to price environmental damage caused by energy consumption into energy prices, such as a carbon tax, and/or by implementing stricter emissions regulations, such as a cap-and-trade system. Such a process would need to be phased in over a sufficiently long period so that citizens and businesses may efficiently adapt, and be revenue neutral such that all increases are refunded back to consumers through tax cuts. In this way, Canada could become a world leader in sustainable development.

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Methodologies

This appendix provides background on the statistical methodology used in this study. This study uses the statistical software packages SPSS 17 and R v. 2.5.1 to perform these analyses. Specifically, Appendix A details calculations, discusses necessary statistical assumptions, and reviews general methodology of the following.

1. Regression analysis
2. Akaike's Information Criterion
3. General regression analysis statistics
4. The concept of suppression
5. Relative importance analysis
6. Limitations of analytical results

Regression Analysis

Multiple regression analysis generates the necessary information to assess how each factor contributes to the explanation of observed variation for each policy subcategory. This study uses the statistical software package SPSS 17 to perform these analyses. The discussion first proceeds by selecting an appropriate subset of factors from a collection of statistically significant, at the 95% level of confidence, groups of factors generated using various regression methods. Once selected, various multiple regression results characterize the nature of the relationship between these significant influential factors and the various policy measures. After characterization, the discussion focuses on a phenomenon known as suppression, which confuses the assessment of each significant influential factor's contribution to explaining the observed variance of the dependent variables. Next, the discussion describes the methodology that accounts for the effects of suppression used to gauge the relative importance of each significant influential factor to predicting respective dependent variables. The appendix concludes by examining several issues that limit the interpretation of these analytical results.

Multiple regression analysis identifies and quantifies the pattern of relationships between many independent (predictor) variables and one dependent (criterion) variable. In the context of this study, the factors influencing environmental performance form the independent variables used to explain the variance observed in the dependent composite environmental index or related policy subcategories. Multivariate techniques, such as multiple regression, control increases in experiment-wise Type I error rates (rejecting the null hypothesis when it is true) that occur when combining several univariate tests, a significant quality because it allows finer-scale findings to emerge (Stevens 2002). Experiment-wise error rates refer to the probability of a Type I error occurring anywhere within the whole analysis, as opposed to a single hypothesis test.

Multiple regression analysis generates an equation, known as the multiple regression equation (eq. A.1). It consists of weighted sums of two or more explanatory variables,

$$Y_i = \beta_0 + \sum_{j=1}^{k} x_{ij}\beta_j + \varepsilon_i . \tag{A.1}$$

The weights, β_j, known as partial regression coefficients, combine to predict scores of the criterion variable that are as close as possible to the observed values. A partial regression coefficient specifies, on average, the amount of change that occurs in the dependent variable per unit change in the explanatory or predictor variable, provided all other explanatory variables are statistically controlled. Selecting appropriate partial regression coefficients minimizes the sum of the squared differences between the predicted and observed values. This technique is the ordinary least squares solution (Stevens 2002; Spicer 2005). It assumes that the error term, ε_i, fulfils several criteria, although the analysis can withstand a certain amount of deviation from these ideal criteria and still yield valid statistical results. These errors must have a mean of zero and must have equal variances across all values of the explanatory variables (i.e., are homoscedastic). Error terms must also be uncorrelated with each other and with the explanatory variables and must be normally distributed (Stevens 2002; Licht 1995; Spicer 2005). Moderate violations of these assumptions are not usually problematic for interpreting results; a researcher checks these assumptions visually with histograms and scatter plots of residuals. Data of this research display only minor variations from the ideal set of assumptions.

Multiple regression analysis may take one of three forms: standard, sequential, and statistical (Tabachnik and Lidell 2007; Spicer 2005; Stevens 2002). These approaches differ only on how the analysis includes additional explanatory variables. With standard multiple regression analysis, all explanatory variables enter the regression equation simultaneously, but each explanatory variable is evaluated as if it was entered into the regression after all other variables. In other words, this type of regression assesses what each explanatory variable adds to the predictability of the criterion that is different from the other explanatory variables. Thus, a significant explanatory variable might appear unimportant because the other variables are masking its presence. With sequential, often referred to as hierarchical, multiple regression analysis, the researcher selects the order that the explanatory variables enter the regression equation, and each variable is assessed in terms of what it adds to the equation at its point of entry. Thus, the challenge lies in ascertaining the correct order of entry into the regression equation for each explanatory variable.

In contrast to standard regression, statistical regression analyses techniques enter explanatory variables based solely on statistical criteria. These techniques use forward selection, backward deletion, or stepwise regression to determine the next explanatory variable for inclusion, or exclusion, in the regression equation (Tabachnik and Lidell 2007; Spicer 2005; Stevens 2002; Licht 1995; Cohen and Cohen 1983). In forward selection, the analysis starts without any explanatory variables entered and adds one at a time based on statistical criteria. Importantly, once an explanatory variable enters the regression equation it can not be removed. Usually, the explanatory variable with the highest simple correlation enters the equation first followed by variables with the largest partial correlations with the dependent variable; thus, the analysis enters additional variables that contribute the most to R^2.

In backward deletion, the analysis starts with all explanatory variables entered and deletes variables one at a time that do not contribute significantly to R^2; thus, this method excludes variables at each step with the smallest partial correlations with the dependent variable. This technique compares a partial F value, calculated for every explanatory variable as if it was the last one entered into the analysis, with an F to remove to determine the next variable to exclude from the analysis.

Stepwise regression offers a compromise between these two procedures in which the analysis starts empty with explanatory variables added if they meet statistical criteria. If the equation contains independent variables, stepwise regression removes the variable with the largest probability of F if the value is larger than p_{out} and recalculates the equation without the variable, repeating the process until no more independent variables are candidates for removal. Then, stepwise regression enters the independent variable not in the equation with the smallest probability of F if the value is smaller than p_{in} and again re-examines all variables in the equation for removal. This process continues until no variables in the equation are candidates for removal and no variables not in the equation are eligible for entry. Consequently, stepwise regression reassesses the importance of each explanatory variable, thus the regression can remove previously included variables that cease contributing significantly to R^2.

Akaike's Information Criterion

This analysis uses stepwise[1] and backward[2] regression techniques to form candidate subsets of influential factors for further investigation. The influential factors form the complete set of independent variables from which one withdraws subsets for multiple regression with the various composite indices, as well as the GHG indicator. Used either singly or in conjunction with one another, these commonly used regression techniques often produce several significant sets of explanatory variables. Consequently, an analyst faces the challenge of selecting the best model from among many candidates.

A commonly used metric for selecting among variable sets is Akaike's Information Criterion (AIC) (Burnham and Anderson 2004; Cetin and Erar 2002; Kabaila 2002), which balances predictive power of the regression equation with parsimony of independent variables. In essence, AIC penalizes a model for adding too many explanatory variables. Minimizing the number of explanatory variables not only reduces experiment-wise Type I error rates by lowering the number of hypothesis tests, it also increases the statistical power thus decreasing the probability of Type II errors, failing to reject the null hypothesis when it is false (Cohen and Cohen 1983: 170). AIC, with a foundation in information theory, selects the most appropriate model based on the loss of Kullback-Leibler information, usually estimated with the maximum likelihood function. In the special case of least squares estimation with normally distributed errors AIC becomes

$$\text{AIC} = n \ln\left(\frac{\text{SSE}}{n}\right) + 2k, \tag{A.2}$$

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[1] In stepwise regression, the equation starts empty and one adds predictors according to statistical criteria until no further significant gains to the explained variance occur (Tabachnick and Fidell 2007; Stevens 2002). This technique constantly reassesses the significance of each predictor, thus it may remove from the equation significant predictors previously identified.

[2] Backward regression starts with all predictors in the equation and deletes them one at a time if they do not add to the explanatory power of the regression (Tabachnick and Fidell 2007; Stevens 2002).

where n is the number of observations, k is the number of parameters in the regression equation including the constant (intercept), and SSE is the sum of squared errors.

According to Burnham and Anderson (2004: 12), researchers often neglect the effects of sample size when applying AIC. Such neglect may lead researchers to conclude that AIC over fit their model by including too many explanatory variables. Therefore, when n/k is less than 40, Burnham and Anderson (2004: 12) recommend using an AIC corrected for sample size (AIC_C),

$$\text{AIC}_\text{C} = \text{AIC} + \frac{2k(k+1)}{n-k-1}. \tag{A.3}$$

As n gets large AIC_C converges to AIC, thus, a researcher should use AIC_C routinely. Therefore, the predictor subset with the smallest (most negative) AIC_C best balances parsimony of included explanatory variables with predictive power of the regression equation, given the size of the sample analyzed, and is the most appropriate subset to carry forward into the next stage of the regression analysis.

Characterization of Significant Influential Factors

With the most appropriate subsets of predictor factors selected, the investigation shifts to how influential these factors are as a group as well as individually. Table 13 contains selected multiple regression statistics from analyses between the subcategories with the most appropriate subsets of predictor factors determined by AIC_C. The complete output from SPSS, from which these statistics are drawn, appears in Appendix B. The very small p-values (<0.05) derived from an F-test indicate that the selected subsets are statistically significant at a 95% level of confidence, meaning these results could only occur by chance one time in twenty.

The sign of the standardized partial regression coefficient (β) indicates how each factor influences the composite index. Essentially, the sign specifies the direction of the relationship between explanatory and dependent variables; a positive value indicates that increases in the factor increase environmental sustainability performance, while a negative one indicates that performance decreases as the factor increases. Energy prices and environmental governance both have positive standardized partial regression coefficients, no matter which subcategory they are associated with, meaning that as the value of these factors increases so does the value of the corresponding composite indices and the underlying environmental performance they measure. Population growth also has a positive standardized regression coefficient, but the factor is only significant for one subcategory, so it does not have an opportunity to switch signs. Higher energy prices not only improve overall performance, they also tend to induce greater energy efficiency, and lower emissions of waste and pollution, including GHG emissions. For example, in countries facing such a challenge, rising energy prices tend to induce better environmental performance through reduced energy consumption or improved pollution control technology.

Table 13: General statistics from the analyses of each subcategory with its subset of significant factors

INDEX	*F*-TEST *P*-VALUE	R^2 [a]	PREDICTORS [b]	STD β [c]	SSCC [d]
Composite Environmental Index	0.0074	0.4201	Energy Prices	0.5609	0.2828
			Environmental Governance	0.5491	0.2710
					0.5538
Energy Efficiency	0.00003	0.6839	Energy Prices	0.5803	0.3248
			Climate	-0.4896	0.2312
					0.5560
Waste and Pollution	0.0011	0.5323	Energy Prices	0.7558	0.5134
			Environmental Governance	0.3779	0.1284
					0.6417
GHG Emissions	0.0000001	0.9380	Climate	0.2616	0.0392
			Population Growth	0.3304	0.0716
			Economic Output	-0.3493	0.0693
			Industrial Structure	-0.1800	0.0200
			Energy Prices	0.9930	0.5368
			Environmental Governance	0.3063	0.0396
					0.7763

a – Coefficient of multiple determination
b – Significance determined at the 95% level of confidence
c – Standardized partial regression coefficient
d – Squared semi-partial correlation coefficient, which sum to R^2 when predictors are uncorrelated

On the other hand, two factors—economic output and industrial structure—possess negative standardized partial regression coefficients. Growing economic output and energy-intensive industrial structures both tend to hinder performance at reducing GHG emissions; economic output through the increased consumption that the affluence allows, and industrial structure through the heightened consumption of energy. As with population growth, these two factors appear for only one subcategory, and so do not have an opportunity for the signs to switch.

Finally, the standardized regression coefficients for climate are the only ones to switch sign depending on the subcategory with which they are associated. Increasing degree days, used to represent climate, are associated with reduced GHG emissions thereby improving performance on the indicator, but is also associated with reduced performance on the energy efficiency subcategory.

The Concept of Suppression

To determine factor importance, analysts often use two measures: standardized partial regression coefficients and squared semi-partial correlation coefficients (Tabachnick and Fidell 2007; Stevens 2002; Licht 1995). Partial regression coefficients specify the amount the dependent variable changes, on average, per unit change in an explanatory variable while statistically controlling all other explanatory variables. When standardized (converted to z-scores), a partial regression coefficient's magnitude indicates the associated factor's relative importance. At the same time, semi-partial correlation coefficients measure the correlation between a specific explanatory variable and the dependent variable while partialling out influences of all other explanatory variables from the specific explanatory variable, but not out of the dependent variable. Thus, squared semi-partial correlation coefficients represent the unique proportion of variance that respective factors explain in the dependent variable, which theoretically allows one to determine the relative importance of each explanatory variable. However, correlated explanatory variables do not necessarily sum to the coefficient of multiple determination, usually totalling to a smaller value. When the sum of the squared semi-partial correlation coefficients is less than the coefficient of multiple determination, the difference is attributable to the proportion of explained variance shared by the explanatory variables (Tabachnick and Fidell 2007: 146). Figure 1 illustrates this situation with a Venn diagram, whereby neither of the squared semi-partial correlation coefficients of the explanatory variables x_1 and x_2 accounts for area c, the shared contribution, thus, the coefficients sum to something less than R^2.

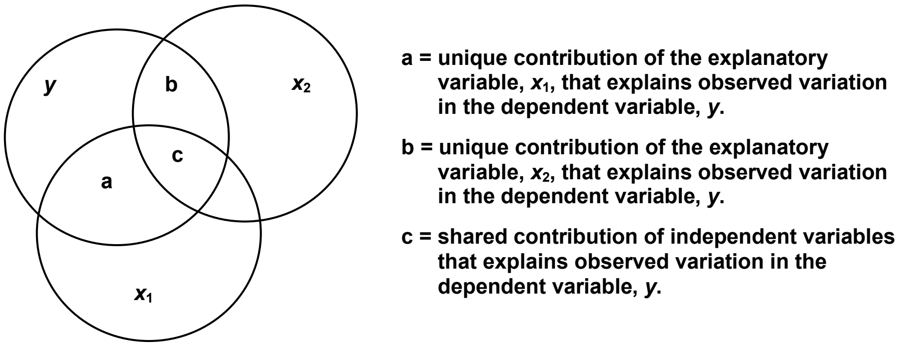

Figure 1: Venn diagram with circles that represent a variable's variance demonstrating how overlapping correlated explanatory variables may produce lower sums of squared semi-partial correlation coefficients than the coefficient of multiple determination

On the other hand, when this sum is larger, a phenomenon known as suppression may be occurring. According to Friedman and Wall (2005), who survey the literature on suppression to reconcile the many different terms used to refer to this phenomenon, suppression is a combination of three different aspects: redundancy, enhancement, and suppression. A redundant explanatory variable, when included in the multiple regression analysis, explains less of the dependent variable's observed variation than one would expect given its correlation, and its standardized partial regression coefficient is also smaller than expected signifying that a redundant explanatory variable is less important than the correlation implies. With an enhancing explanatory variable the amount of the explained variation and the standardized partial regression coefficient are both larger than one would expect given the correlation between the variables, thus demonstrating that an enhancing explanatory variable is more important than indicated by the correlation. Meanwhile a suppressor explanatory variable's standardized partial regression coefficient is larger than its corresponding correlation with the dependent variable, usually because the correlation is near zero, and the overall explained variance is smaller than if the situation were enhancement, but still larger than without the suppressor variable (Friedman and Wall 2005; Tabachnick and Fidell 2007).

Both enhancement and suppression variables increase the magnitude of the explained variation of a dependent variable. Such variables accomplish this feat by removing, or suppressing, irrelevant variation not associated with the dependent variable in one or more of the other explanatory variables (Tabachnick and Fidell 2007; Cohen and Cohen 1983; Stevens 2002). Clearly, analysts should exclude redundant variables from the regression analysis because they add no further information. However, both enhancement and suppression variables are desirable because they increase the explanatory power of the analysis by increasing the explained portion of a dependent variable's variance.

Many efforts aimed at identifying suppression variables typically discuss methods involving only two predictor variables (Velicer 1978; Hamilton 1987; Malgady 1987; Smith et al. 1992; Sharpe and Roberts 1997; Maassen and Bakker 2001; Shieh 2001; Friedman and Wall 2005). Nevertheless, one recent effort (Shieh 2006) develops a method for more than two predictor variables. Essentially, the candidate variable forms one explanatory variable while the analyst treats the group of other explanatory variables as the second explanatory variable to calculate the Γ (pronounced gamma) statistic, defined as

$$\Gamma = r_{Y(j.h)} / r_{Yj}, \tag{A.4}$$

where $r_{Y(j.h)}$ represents the semi-partial correlation coefficient of y with x_j, which controls for all other x_h, and r_{Yj} represents the coefficient of correlation between y and x_j. When squared, the ratio Γ determines how the unique variation that the specified explanatory variable explains on the dependent variable changes from the situation of no other predictors to one where all predicators are present. Enhancement occurs when Γ^2 is greater than 1 while suppression occurs when Γ^2 is greater than 1 - R^2_{jh}, but still less than 1, where R^2_{jh} represents the coefficient of multiple determination for x_j with ($x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_p$), that is the set of all other explanatory variables not including x_j.

Table 14 applies this framework to the two subcategories with a sum of squared semi-partial correlation coefficients greater than R^2 and with more than one predictor variable. This suppression analysis provides three benefits. First, the nature of how enhancing and suppressor variables remove variation from other explanatory variables may have implications for policy recommendations directed at improving a country's environmental sustainability performance. Second, suppression analysis helps to identify, in conjunction with the analysis of multicollinearity discussed in the limitations section, redundant variables that interfere with the multiple regression analysis. As table 14 shows, the analysis uncovers no redundant variables, with all explanatory variables classified as enhancement.

Table 14: Analyzing and identifying the types of suppression

INDEX	X_1	X_2	Γ^2	$1 - R_{JH}^2$	TYPE OF SUPPRESSION
Composite Environmental Index	Energy Prices	Constant, Environmental Governance	1.896	0.899	Enhancement
	Environmental Governance	Constant, Energy Prices	1.973	0.899	Enhancement
Waste and Pollution	Environmental Governance	Constant, Energy Prices	6.800	0.899	Enhancement
	Energy Prices	Constant, Environmental Governance	1.271	0.899	Enhancement

Suppression: $1 - R^2_{jh} < \Gamma^2 < 1$

Enhancement: $\Gamma^2 > 1$

$\Gamma = r_{Y(j.h)} / r_{Yj}$,

Γ^2 represents how the unique variation that the specified explanatory variable explains on the dependent variable changes from the situation of no other predictors to one where all predicators are present.

R^2_{jh} represents the coefficient of multiple determination for x_j with ($x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_p$), that is the set of all other explanatory variables not including x_j.

Lastly, such an analysis supplies further information for interpreting multiple regression statistics, specifically, the squared semi-partial correlation coefficients contained in table 13. These coefficients, which should sum to the coefficient of multiple determination, but, in these two cases, produce a greater summand. Referring to table 13, the squared semi-partial correlation coefficients for the Composite Environmental Index produce a summand about 32% greater than the corresponding coefficient of multiple determination. Similarly, the squared semi-partial correlation coefficients pertaining to the waste and pollution category provide a summand that is larger than the corresponding coefficient of multiple determination by about 20%. Thus, suppression is producing effects that influence and confound the assessment of relative importance of each explanatory factory to environmental sustainability performance.

Relative Importance of Significant Influential Factors

Once characterized, the question of importance of specific factors becomes relevant. This study uses the statistical software package R v. 2.5.1 to perform this analysis. To determine factor importance, analysts often use two measures from table 13: standardized partial regression coefficients and squared semi-partial correlation coefficients (Tabachnick and Fidell 2007; Stevens 2002; Licht 1995). However, correlated explanatory variables do not necessarily sum to the coefficient of multiple determination, usually totalling to a smaller value. When the sum of the squared semi-partial correlation coefficients is less than the coefficient of multiple determination, the difference is attributable to the proportion of explained variance shared by the explanatory variables (Tabachnick and Fidell 2007: 146). On the other hand, when this sum is larger, a phenomenon known as suppression may be occurring. Appendix A.4 contains a greater discourse on the concept of suppression, as well as the results of an analysis for the presence of suppression among the factors.

These effects of suppression, arising from correlation among the variables, suggest that standardized partial regression coefficients and squared semi-partial correlation coefficients may provide ambiguous information, which may lead to faulty conclusions. The limitations section explores this phenomenon, known as multicollinearity, further. Moreover, several regression techniques credit shared contribution to variables entered first, while suppressor variables depend on the presence of other variables, as well as the correlation between them, before its effects can manifest. Therefore, the order in which a variable enters the regression analysis affects the size of the contribution attributed to it. Averaging the percentage contribution of each explanatory variable from every ordering of the variables produces a useful estimate of the proportion each variable contributes to the prediction of the dependent variable (Gromping 2007, 2006; Soofi et al. 2000; Kruskal 1987a, 1987b; Lindman et al. 1980). Sequential, or hierarchical, regression analysis (briefly described in Appendix A.1) in which the analyst specifies the order of variable entry provides a method for achieving this objective. Therefore, this method is used in this study to assess the relative importance of the significant factors for each subcategory.

Limitations of Analytical Results

With the analytical scrutiny of the influential factors complete, one must now consider issues that may be limiting the interpretive capacity of these methods. Correlations among and between explanatory variables, termed multicollinearity, may cause problems with multiple regression. Multicollinearity reduces the ability of multiple regression analysis to discern effects (Stevens 2002; Licht 1995), and as it escalates, three problems become evident (Stevens 2002; Tabachnick and Fidell 2007). The multiple correlation coefficient, R, and the coefficient of multiple determination, R^2, that depends on it both become very unstable with excessive levels of multicollinearity. Escalating multicollinearity also increases the volatility of partial regression coefficients such that the corresponding confidence intervals become larger, thus reducing the likelihood that such variables are statistically significant as well as also confounding the effects of explanatory variables rendering it difficult to determine the importance of individual explanatory variables.

A simple set of diagnostic statistics allows a researcher to determine the level of multicollinearity a data set may contain. SPSS produces diagnostics, known as a condition index and associated variance proportions, proposed by Belsley et al. (1980). Each dimension[3] of the regression equation possesses a condition index while the variance proportions indicate the amount of variation a specific dimension measured by a condition index induces in each explanatory variable estimated parameters. A condition index measures the dependency of one variable on the others, with increasing values associated with larger standard errors in the estimation of variable parameters. As these standard errors become large, estimated parameters become highly uncertain.

Multicollinearity becomes problematic, that is crosses some critical threshold whereby the issues discussed above become apparent, when a large condition index contributes strongly to the variance of two or more explanatory variables. Specifically, Belsley et al. (1980) suggest that the level of multicollinearity crosses this critical threshold when a condition index value greater than 30 occurs in conjunction with variance proportions greater than 0.5 for two or more explanatory variables. Clearly, multicollinearity is not an issue for three of the four subcategories since only GHG emissions has a maximum condition index greater than 30 (table 15). However, this dimension only strongly induces variation in one explanatory variable (environmental governance) as determined by a variance proportion greater than 0.5. Consequently, the level of multicollinearity in the data set is just approaching the critical threshold whereby effects would become apparent.

As mentioned, highly correlated explanatory variables likely explain a portion of the same variance on the dependent variable, making one somewhat redundant. Standard multiple regression techniques do not attribute this redundant variance as an independent contribution to any explanatory variable; thus, arises the problem to which explanatory variable such variance should be attributed. However, the presence of suppression effects, which depend highly on the order of variable entry into the regression equation, also alters how the analysis allocates this variance. To mitigate these issues, as this study does, when exploring the relative importance of

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[3] The number of primary elements that parsimoniously partitions the total observed variance in a data set indicates the dimensionality of the data structure. Formally referred to as eigenvectors, these elements are linear combinations that specify how the variables load onto them, with the variance they explain known as eigenvalues. Moreover, these eigenvectors are uncorrelated with and independent of each other and, therefore, are orthogonal; each component explains unique variation not captured by other linear combinations. The number of eigenvectors that explains all the variance is the rank, or true dimensionality, of the variable set. Each eigenvector has a corresponding condition index, the value used, in conjunction with variance proportions, to assess multicollinearity.

explanatory variables, a researcher may average each explanatory variable's contribution to the regression equation over every ordering of the variables (Gromping 2007, 2006; Soofi et al. 2000; Kruskal 1987a, 1987b; Lindman et al. 1980).

Table 15: Determining the level of multicollinearity in the data set

INDEX	MAXIMUM CONDITION INDEX	PREDICTORS	VARIANCE PROPORTIONS
Composite Environmental Index	25.6	Energy Prices	0.344
		Environmental Governance	0.908
Energy Efficiency	13.4	Energy Prices	0.776
		Climate	0.385
Waste and Pollution	25.6	Energy Prices	0.344
		Environmental Governance	0.908
GHG Emissions	52.4	Climate	0.128
		Population Growth	0.088
		Economic Output	0.047
		Industrial Structure	0.365
		Energy Prices	0.104
		Environmental Governance	0.839

Note: Multicollinearity starts to become problematic if the maximum condition index is > 30 in conjunction with variance proportions > 0.5 for at least two predictors (Belsley et al. 1980).

Specification errors may also affect the regression analysis. These errors, which lead to difficulty achieving statistical significance, arise by not including all relevant explanatory variables, or by including irrelevant ones, in the regression analysis. Indeed, including, or excluding, even one explanatory variable may substantially alter regression statistics (Licht 1995). Thoroughly grounding the selection process for explanatory factors in a solid theoretical framework mitigates the effects of selection error, as does using a technique that balances predictive power with parsimony of independent variables, in this case AIC_C, to select the most appropriate set of variables.

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Regression Analyses Software Output

This appendix provides SPSS output from the regression analyses of this study. Specifically, Appendix B presents the raw output from SPSS (version 17) for various results from both multiple and univariate regressions. The output includes

- ANOVA (ANalysis Of VAriance) results that assess the significance of the relationships among explanatory and dependent variables,
- model summaries that describe the variance explained by the independent variables, and
- coefficients used to calculate predicted values for the dependent variable, and the various correlations between explanatory and dependent variables that arise from multiple regression.

Multiple Regression ANOVA Results

Composite Environmental Index

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	F	SIG.
1	Regression	.045	2	.022	6.520	.007
	Residual	.062	18	.003		
	Total	.107	20			

Energy Efficiency Subcategory

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	F	SIG.
1	Regression	.688	2	.344	19.470	.00003
	Residual	.318	18	.018		
	Total	1.007	20			

Waste and Pollution Subcategory

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	F	SIG.
1	Regression	.141	2	.070	10.241	.001
	Residual	.124	18	.007		
	Total	.264	20			

Greenhouse Gas Emissions Indicator

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	F	SIG.
1	Regression	1.508	6	.251	35.292	.0000001
	Residual	.100	14	.007		
	Total	1.608	20			

Multiple Regression Model Summaries

Composite Environmental Index

MODEL	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.648	.420	.356	.058636

Energy Efficiency Subcategory

MODEL	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.827	.684	.649	.132968

Waste and Pollution Subcategory

MODEL	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.730	.532	.480	.082894

Greenhouse Gas Emissions Indicator

MODEL	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.968	.938	.911	.084401

Multiple Regression Coefficients and Correlations

Composite Environmental Index

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	.067	.150		.448	.659			
	Energy Prices	.000215	.000072	.561	2.963	.008	.386	.573	.532
	Environmental Governance	.006	.002	.549	2.900	.010	.371	.564	.521

Energy Efficiency Subcategory

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	.518	.183		2.829	.011			
	Energy Prices	.001	.0002	.580	4.300	.0004	.673	.712	.570
	Climate	-.0001	.00003	-.490	-3.628	.002	-.599	-.650	-.481

Waste and Pollution Subcategory

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	-.072	.212		-.342	.736			
	Energy Prices	.000455	.000102	.756	4.445	.000313	.636	.723	.717
	Environmental Governance	.006	.003	.378	2.223	.039	.137	.464	.358

Greenhouse Gas Emissions Indicator

MODEL		UNSTANDARDIZED COEFFICIENTS		STANDARDIZED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	-1.019	.303		-3.357	.005			
	Climate (total degree days)	.000074	.000025	.262	2.975	.010	.051	.622	.198
	Population Growth	18.714	4.656	.330	4.019	.001	-.293	.732	.267
	Economic Output	-.000016	.000004	-.349	-3.954	.001	-.537	-.726	-.263
	Industrial Structure	-2.340	1.102	-.180	-2.123	.052	-.138	-.494	-.141
	Energy Prices	.001	.000134	.993	11.008	.000000028	.804	.947	.733
	Environmental Governance	.013	.004	.306	2.989	.010	.033	.624	.199