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THE INFLUENCE OF ENVIRONMENTAL TAX AND TECHNOLOGY ON DIFFERENT AIR POLLUTION EMISSIONS IN OECD COUNTRIES

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Abstract

Although countries continuously employ taxation and technological measures to control air pollution in the Organization for Economic Co-operation and Development, the results of these practices should be evaluated to determine whether they reach their intended outcomes. This study used panel autoregressive distributed lag model to establish how environmental taxes and technology affects the emission of air pollutants (nitrogen oxides, Carbon dioxide, and particulate matter 2.5). Using secondary data present in the OECD Database and The World Bank, EViews panel was derived to create 3 model in which each of the three variables would be sufficiently explained by environmental tax, abatement technology, patented technology, gross domestic product, and population. In these models, the carbon dioxide was found to exhibit a long-term relationship with these independent variables unlike the other two dependent variables. However, in all the cases, both environmental tax and technology significantly affected the emissions of air pollutant. Increments in the technology, annual growth rate, and taxes demonstrated positive relationships. In this regard, it was deduced that governments should take charge in enforcing stiffer taxation measures as population increases to account for economic growth and control existing pollution levels.

Keywords

Auto-regressive distributed lag, Environmental tax, carbon dioxide, nitrogen oxides, particulate matter 2.5, gross domestic product, technology

1. INTRODUCTION

The OECD has taken the lead in international attempts addressing environmental issues; their air pollution reduction plans are some of the most wide-ranging and effective global responses. To help improve air quality and address contamination, a myriad of technologies have been established and used in OECD nations. Each country has favored its own technology, aligned with their specific atmospheric requirements. . In essence, air pollution can be caused by a variety of sources, including factories, power plants, automobiles, and airplanes, in which carbon dioxide, nitrogen oxide, and sulfur dioxide emissions may be attributed to burning fossil fuels.

Burning fossil fuels is the primary source of carbon dioxide pollution. Vehicles running on petrol or diesel release CO_2 into the atmosphere, forming a thick coating that affects how solar radiation is trapped. Burning charcoal and firewood also produces CO_2 with deforestation reducing the number of plants available to absorb this gas, leading to an increase in emissions. These activities increase the atmospheric CO_2 levels, contributing to climate change. Similarly, NO_2 emissions are a considerable source of environmental contamination, which are attributed to the combustion of fossil fuels, particularly vehicles. . A serious repercussion of NO_2 is ozone layer depletion, increasing UV radiation and associated health issues. These pollutants interact with oxygen, water and other chemicals in the atmosphere, forming nitric acid and acid rain which damages iron sheets and causes plant diseases. Finally, air pollution is often caused by particles, both natural and human made, released into the atmosphere. Volcanoes, dust storms, sea spray, and forest fires are examples of natural pollutants. Burning fossil fuels such as coal, oil, and natural gas is the most common source of manufactured particulate matter (PM). Different particles can have various sizes, ranging from tiny aerosols to larger pieces like sand or soot. Depending on its size and composition, PM can have various impacts on the environment. For instance, smaller particulates may be inhaled, potentially leading to breathing difficulties. In comparison, larger, highly concentrated particles can cause eyes, nose, and throat irritation, even potentially reducing visibility, eroding soil surfaces, and contributing to smog formation, as well as affecting climate change through absorbing and scattering the sun's rays. Particulate waste includes ash, dust, fumes, mist and smoke that come from various sources such as manufacturing and combustion processes or the burning of solid waste. Additionally, pollutants such as ammonia, volatile organic compounds (VOCs), ground-level ozone and heavy metals like lead and mercury can also be released into the atmosphere.

Humans are also a source of atmospheric pollutants, including agriculture, motor vehicle use, and industrial operations. Fossil fuel combustion and other emissions have increased damage to the environment, eventually causing danger to all life on Earth. Fortunately,, the implementation of renewable energy has had a positive effect, leading to a considerable reduction in these emissions. which could eventually damage the environment irreparably. It can lead to respiratory issues, heart disease, cancer, and premature death and also cause acid rain which harms forests and lakes, contributing to global warming. Fortunately, there are numerous methods to limit air pollution. By using renewable energy sources such as solar or wind power instead of fossil fuels and driving less often, dioxide emissions and other toxic pollutants have reduced considerably. Planting trees is another strategy promoting CO_2 absorption Air pollution costs $8.1 trillion, which amounts to 6.1% of the global GDP. Pollution is more severe in urban areas compared to rural areas. Industrialization and urbanization, which are major causes of air pollution in developed countries, pollution in developed countries is higher than in developing countries.

Governments must lead environmental sustainability. Some nations use market-based strategies reflecting environmental concerns rather than instigating green taxes. Environmental taxes average 2% of revenue in most OECD countries. Government taxes concerning climate change can led to a reduction in atmospheric pollutants; wo-thirds of environmental tax revenue comes from carbon taxes on fossil fuels like coal, oil, and gas, which target energy use. The taxes discourage harmful emissions, promoting greener alternatives while funding renewable energy sources to prevents overexploitation and promote sustainability. Pollution and resource use are taxed. Taxing land and water use, polluting emissions, and environmentally damaging actions like burning fossil fuels for travel has been recommended. . Environmental taxes may be reflected in product prices. Funding green infrastructure and public transportation may reduce pollution and improve quality of life, changing behavior via financial incentive. Using the revenue could also boost renewable energy employment. There are also Pigouvian and green taxes, which target activities with harmful effects even if they do not produce externalities. Beneficiaries should pay for protection, corporations should pay for damage, and those who might harm the environment should pay for prevention.

Technology can reduce emissions into the atmosphere. Among the primary contaminants of concern are particulate matter, ground-level ozone, nitrogen oxides, and sulfur dioxide. Commonly used technologies include preventing pollutant release or collects it after release. As better understanding of the health and environmental effects of air pollution occurs, the problem becomes more evident. Utilizing air pollution abatement technology is now considered essential in maintaining public and environmental health. It purifies the air, improving economic productivity and increasing public health. These processes can also create more jobs in this sector.

In light of the issues, this study seeks to establish a model that can be used in determining whether taxing and technology would impact the amount of pollutants in the atmosphere. The following sections will describe the variables used in this study as applied in other studies before explaining its methods and outcomes.

2. LITERATURE REVIEW

2.1. Environmental Tax

Studies examining the effects of environmental taxes on air pollution have been numerous. A Computable General Equilibrium (CGE) model was can be used to measure the effects of an Environmental Protection Tax (EPT) on pollution. Studies have employed the same model to assess EPT's impacts on various industries. An evaluative model was developed to measure the overall effect of environmental taxes on pollution, combining various approaches and offering recommendations for pollution reduction. The CGE model and a Bayesian optimization algorithm were then adopted to push economic growth while maintaining environmental sustainability.

Some studies note suggest the importance of the critical nexus between economic viability and environmental sustainability. It was also asserted that countries with Environmental Protection Tax (EPT) boast more stable economies. Levying environmental taxes would aid in reducing emissions, providing a positive boost to the Gross Domestic Product (GDP). Revenue generation as a key factor for development powered by these schemes. ; effectiveness is an imperative element of taxation policies.

Environmental taxes have been demonstrated to drive the development of a habitable environment. The proper formulation of tax policies is essential to ensure sustainability across the long term. The are considered vital for future progress. There is a link between responsibility and sustainability, as well as imposing taxes on those who pollute. Companies that pollute will be expected to pay principally, obligating those who damage nature to pay for it.

Reception of green taxes varied by country. It can help reduce air pollutants regardless. Studies in Europe, Canada and the US demonstrate that such policies have been successful in improving environmental standards In addition, research suggests that environmental taxes have had positive impacts in Sweden and Japan, and are likely to become increasingly important in the near future. Carbon taxes are essential for cutting down on the emission of harmful greenhouse gases. Figures have proven a significant decrease in carbon emissions when taxes have been implemented. A comparative study showing the effects of carbon taxes on the US policy regarding environmental protection. In addition, carbon taxes are assumed to decrease greenhouse gases. These points and perspectives –suggest imposing carbon taxes is key to reducing toxic gas emissions.

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Carbon taxes help minimize energy use. There has been a notable decrease in Japan's energy consumption following their levy. Taxes are essential for encouraging more conservation measures. There is a strong link between them. The are important for fuel consumption. Carbon taxes assist in cutting back energy usage, improving air quality in the process.

2.2. Environmental Technology

Renewable energy is imperative to mitigating air pollution via waste-to-energy (WtE) technologies such as gasification, incineration, landfill gas recovery and composting. (Anhydrous ethanol is another recommended renewable energy source. 2018 saw a considerable surge in investment for renewable energy sources, reaching $18 billion 2019.

Solar energy is getting increased attention for its inexhaustible nature. It may alleviate fossil fuel use globally. The increased demand for fossil fuels has increased the release of CO, $_2$particulate matter (PM2.5), and nitrous oxide (NO). Over 70% of global air pollution is caused by vehicles. Plant life is dying. Causes of global pollution include the rapid expansion of the automobile industry in India and other developing countries and has only worsened over time.

2.3. Air Pollution

There is a link between economic growth and pollution, such as the old connection. . A study exploring the association between CO_2 and economic factors such as gross domestic product (GDP) per capita, energy use and urbanization. In previous studies four main forms of relationship between financial growth and environmental destruction were identified: inverted U-shaped, consistently rising, U-shaped and N-shaped.

The Environmental Kuznets Curve (EKC) theory suggests an inverted U-shaped relationship between environmental degradation and economic development. Industrial activity and economic activity work together; however, with improved technology and services this stabilizes and gradually decreases. The exact shape of this relationship can vary depending on the period, location, or income of a country. CO_2 follows a monotonically increasing pattern whereas NO_2 and CO show an inverted U-shape.

The world's population is predicted to reach 9.8 billion by 2050, with significant impact the environment via air pollution and increased temperatures, with the Intergovernmental panel on Climate Change (IPCC) predicts a 2.6°C increase in global temperature by the end of the century, bringing about more extreme weather conditions such as heat waves, droughts and floods. The US is expected to see an increase of 70 million. The. Increased temperatures will speed the formation of ground-level ozone, leading to even worse air pollution. It is evident that human activity has had an immense impact on our environment and this increasing population only exacerbates the strain on natural resources and the degradation of the planet.

The issue of population growth and its consequences on the environment is pertinent to developing and developed countries. Increased air contamination leads to numerous respiratory illnesses, exacerbating-existing medical conditions such as asthma, bronchitis, heart disease, allergies, and even lung cancer.

2.4. Hypothesis

The following hypotheses were addressed in this study:

1. Environmental taxes significantly impact air pollution emissions such as NO, CO_2, Pm2.5
2. Environmental technology significantly affects air pollution emissions like NO, CO_2, and Pm2.5
3. The annual growth rate (GDP) and population size (OP) are relatively correlated to air pollution emissions (NO, CO_2, Pm2.5) in the short- and long-term.

3. RESEARCH METHODOLOGY

3.1. Variables

Variables considered influential in air pollutant emissions are presented in Table 1.

Table 1: explanation of variables

Code	Meaning
ET_OC	Overall OECD Environmental tax
PAT_OC	Overall OECD Patents of air pollution technology
ABAT_OC	Overall OECD Air pollution abatement technology
GDP_OC	Overall OECD Gross Domestic Product
OP_OC	Overall OECD Population Size
CO_OC	Carbon monoxide
NO_OC	Nitrous oxides
CO2_OC	Carbon dioxide
PM2.5_OC	Particulate Matter

3.2. Model Specification

The Panel Autoregressive Distributed Lag (ARDL) method utilizes the lag period to show the correlation between different variables across both short-term and long-term periods. This approach is particularly effective in addressing possible issues of endogeneity between the error terms and independent variables.

The ARDL panel was used to model the interaction of NO_OC, CO2_OC, or PM2.5_OC with ET_OC, PAT_OC, ABAT_OC as the independent variables and OP and GDP as the control ones. The Akaike info criterion served as the basis for choosing an appropriate model. The ordinary coefficient covariance matrix was then used for estimating the variables in the E-views ARDL modelling. For each region, an optimum number of lags were determined concerning each of the dependent variables through analyzing PAT_OC, OP_OC, CO2_OC, GDP_OC, ET_OC, CO_OC and ABAT_OC. Significant results at $p<0.05$ were obtained from all models upon completion of the bound test. As a result of this test's outcome f-statistics value below I (0)'s lower bound demonstrating there being no long-term correlation among variables; thus, confirming that vector error correction model (VECM) need not be applied whilst ARDL is suffice for this modeling task. While for cases where f-statistic values exceed I (1), it means that long-run relationships exist between them.

3.2.1. CO2

For all variables other than ABAT_OC, the appropriate lag length for this LNCO2 _OC is one ag as shown in Table 2.

Table 2: CO2 in OECD on ARDL

Selected Model: ARDL(1, 1, 1, 0, 1, 1, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LNCO2_OC(-1)	0.941750	0.010745	87.64925	0.0000
ET_OC	-3.31E-06	1.38E-06	-2.399936	0.0166
ET_OC(-1)	2.91E-06	1.40E-06	2.083480	0.0375
PAT_OC	3.72E-05	6.83E-06	5.441387	0.0000
PAT_OC(-1)	-4.05E-05	5.86E-06	-6.914211	0.0000
ABAT_OC	3.36E-05	1.96E-05	1.713949	0.0869
LNOP_OC	0.963479	0.017804	54.11712	0.0000
LNOP_OC(-1)	-0.907585	0.020482	-44.31042	0.0000
GDP_OC	1.08E-13	1.80E-14	5.994801	0.0000
GDP_OC(-1)	-1.10E-13	1.86E-14	-5.910910	0.0000
LNCO_OC	0.078743	0.011547	6.819230	0.0000
LNCO_OC(-1)	-0.075322	0.011715	-6.429465	0.0000
C	-0.265904	0.089591	-2.967971	0.0031
R-squared	0.992804	Mean dependent var		11.52131
Adjusted R-squared	0.992693	S.D. dependent var		1.588780

The substituted and cointegrated values from ARDL Table 2 are in Equation 1.

Equation 1: Short-term and long-term effects of ET and technology on CO2 in OECD countries

Substituted Coefficients: These are the substituted values from the ARDL Table *2*.
========================
LNCO2_OC = 0.941750096073*LNCO2_OC(-1) - 3.30516249994e-06*ET_OC + 2.90994884642e-06*ET_OC(-1) + 3.71791710299e-05*PAT_OC - 4.04859358514e-05*PAT_OC(-1) + 3.36070663641e-05*ABAT_OC + 0.963479104526*LNOP_OC - 0.907585031613*LNOP_OC(-1) + 1.07730077941e-13*GDP_OC - 1.09975273217e-13*GDP_OC(-1) + 0.0787429132257*LNCO_OC - 0.0753224652197*LNCO_OC(-1) - 0.265904136175

Cointegrating Equation:
D(LNCO2_OC) = -0.058249903927*(LNCO2_OC (-1) - (-0.00000678*ET_OC(-1) - 0.00005677*PAT_OC(-1) + 0.00057695*ABAT_OC + 0.95955648*LNOP_OC(-1) - 0.00000000*GDP_OC(-1) + 0.05872023*LNCO_OC(-1) - 4.56488540))

ECM

Table 3: Error Correction Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002080	0.013422	0.154941	0.8769
D(ET_OC(-1))	8.89E-07	3.78E-06	0.234806	0.8144
D(PAT_OC(-1))	-1.02E-05	2.92E-05	-0.348812	0.7273
D(ABAT_OC(-1))	6.44E-05	0.000146	0.439988	0.6601
D(LNOP_OC(-1))	0.089080	0.055218	1.613239	0.1071
D(GDP_OC(-1))	-2.59E-14	5.15E-14	-0.503308	0.6149
D(LNCO_OC(-1))	0.001598	0.031740	0.050355	0.9599
ECM(-1)	-0.089877	0.029699	-3.026244	0.0026
R-squared	0.012563	Mean dependent var		0.001488
Adjusted R-squared	0.003678	S.D. dependent var		0.375954

Equation 2: Corrected equation for CO2 in the long term

```
Substituted Coefficients: These are the substituted values from the ECM.
Substituted Coefficients:
=========================
D(LNCO2_OC) = 0.00207958191528 + 8.88680574699e-07*D(ET_OC (-1)) -
1.02001223694e-05*D(PAT_OC(-1)) + 6.44104413899e-05*D(ABAT_OC(-1)) +
0.0890795505045*D(LNOP_OC(-1)) - 2.59438923744e-14*D(GDP_OC(-1)) +
0.00159826868453*D(LNCO_OC(-1)) - 0.0898769057394*ECM(-1)
```

On the Table 4, the bound test showed that the relationship is long-term because the ARDL f-statistics value (5.10341) was greater than the outbound value (3.28).

Table 4: CO2 on Bound Test

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET_OC	-6.78E-06	8.68E-06	-0.781772	0.4346
PAT_OC	-5.68E-05	7.10E-05	-0.800066	0.4239
ABAT_OC	0.000577	0.000354	1.629824	0.1035
LNOP_OC	0.959556	0.089263	10.74975	0.0000
GDP_OC	-3.85E-14	6.72E-14	-0.573469	0.5665
LNCO_OC	0.058720	0.069999	0.838877	0.4018
C	-4.564885	1.363358	-3.348267	0.0009

EC = LNCO2_OC - (-0.0000*ET_OC -0.0001*PAT_OC + 0.0006*ABAT_OC + 0.9596*LNOP_OC -0.0000*GDP_OC + 0.0587*LNCO_OC - 4.5649)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	5.103407	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

3.2.2. NO

Based on the evaluation, a single lag was chosen for all variables except ABAT, which had no lag. The remaining variables were important. Table 7 shows that the Akaike info criterion (AIC) (0.83045) was used for this evaluation because both SIC (0.894175) and HQC (0.854914) were higher. For all the variables except ABAT, the model chosen for the LNNO was lag (1).

Equation 3: *Effects of ET and technology on NO in OECD countries in short and long term*

Since the values f-statistics in Table 6 for the ARDL model were between I (0) at 2.39 for the inbound and I (1) at 3.38 for the outbound, the bound test indicated inconclusive outcomes.

```
Substituted Coefficients: These are the substituted values from the ARDL Table 7.
=========================
LNNO_OC = 0.960171939401*LNNO_OC(-1) + 9.44836943156e-06*ET_OC -
7.91228011845e-06*ET_OC(-1) - 3.86890483283e-05*PAT_OC + 3.138190246e-
05*PAT_OC(-1) - 2.7386840296e-06*ABAT_OC - 0.162189097432*LNOP_OC +
0.151570629112*LNOP_OC(-1) + 2.61235421078e-13*GDP_OC - 2.65315442013e-
13*GDP_OC(-1) + 0.377533886193

Cointegrating Equation:
D(LNNO_OC) = -0.039828060599*(LNNO_OC (-1) - (0.00003857*ET_OC(-1) -
0.00018347*PAT_OC(-1) -0.00006876*ABAT_OC -0.26660772*LNOP_OC(-1) -
0.00000000*GDP_OC(-1) + 9.47909289))
```

3.2.3. PM2.5

The selected model shown in Table 5 indicates the lags for PAT_OC, LNOP_OC, and GDP_OC only with R-squared and adjusted R-squared surpassing the 93.3% mark.

Table 5: ARDL LNPM2.5_OC

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LNPM2_5_OC(-1)	0.968772	0.010551	91.81471	0.0000
ET_OC	1.53E-06	1.48E-06	1.033383	0.3017
PAT_OC	5.33E-05	2.11E-05	2.519156	0.0120
PAT_OC(-1)	-6.41E-05	1.81E-05	-3.534813	0.0004
ABAT_OC	6.88E-06	6.15E-05	0.111886	0.9109
LNOP_OC	-0.429777	0.052696	-8.155784	0.0000
LNOP_OC(-1)	0.409324	0.052661	7.772849	0.0000
GDP_OC	1.08E-13	4.86E-14	2.218082	0.0268
GDP_OC(-1)	-1.07E-13	4.95E-14	-2.151874	0.0317
C	0.438597	0.235916	1.859121	0.0634

The coefficients for each variable from the ARDL at the level and first difference have been substituted and cointegrated in Equation 2-b-II.

Equation 4: Effects of ET and technology on PM.5 with OECD in short and long term

```
Substituted Coefficients: These are the substituted values from the ARDL Table 6.
========================
LNPM2_5_OC = 0.968771538847*LNPM2_5_OC(-1) + 1.52567320769e-06*ET_OC +
5.32667663141e-05*PAT_OC - 6.41413925716e-05*PAT_OC(-1) + 6.88286789294e-
06*ABAT_OC - 0.429776567475*LNOP_OC + 0.409323582017*LNOP_OC(-1) +
1.07901103947e-13*GDP_OC - 1.065346416e-13*GDP_OC(-1) + 0.438596573308

Cointegrating Equation:
D(LNPM2_5_OC) = 0.438596573307 -0.031228461153*(LNPM2_5_OC(-1) -
(0.00004886*ET_OC -0.00034823*PAT_OC(-1) + 0.00022040*ABAT_OC -
0.65494695*LNOP_OC(-1) + 0.00000000*GDP_OC(-1)))
```

On the bound test, no long-term correlation was found in this model, as the F-statistic value (1.857616) was below the threshold I (0) of 2.55.

Table 6: LNNO in OECD on Bound Test

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET_OC	3.86E-05	3.09E-05	1.249613	0.2118
PAT_OC	-0.000183	0.000267	-0.688349	0.4914
ABAT_OC	-6.88E-05	0.001292	-0.053207	0.9576
LNOP_OC	-0.266608	0.337247	-0.790540	0.4294
GDP_OC	-1.02E-13	2.66E-13	-0.385514	0.7000
C	9.479093	5.329201	1.778708	0.0757

EC = LNNO_OC - (0.0000*ET_OC -0.0002*PAT_OC -0.0001*ABAT_OC -0.2666*LNOP_OC -0.0000*GDP_OC + 9.4791)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	3.116268	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

3.3. Data Sources

After determining the variables, online archives and databases were assessed for information on population, GDP, air pollution emissions (NO, CO2, and PM2.5), abatement technology, patents issued for air pollution technologies, and environmental taxes. Currency-stabilized data for exchange rate fluctuations were available via the World Bank and OECD databases. The same data from the OECD is suitable for EViews analysis. Data collection involved three options, all of which had missing information.

330 observations per variable were compiled from the aforementioned data sources and presented in a panel format. Timeline values used interpolation with EViews or auto-regression to provide a gap analysis. 2020 and 2021 were absent from the timeline and thus considered unusable. As such, predictions were made after determining whether or not the available data points were statistically significant for autoregression. In the other examples, Reviews interpolated the missing data inside the timeline based on the existing data points. These methods enabled the completion of the data set and creation of entities that could be used for cross-regional and cross-temporal regression.

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4. EMPIRICAL RESULTS

4.1. Descriptive Results

Table 7: Descriptive statistics

	CO2_OC	ET_OC	PAT_OC	ABAT_OC	OP_OC	GDP_OC	CO_OC	PM25_OC	NO_OC
Mean	350192.751...	19018.6729...	1383.13583...	316.394306...	34041289.4...	115541064...	3796.65349...	260.936846...	1161.65604...
Median	67401.09	8058.6085	166.06	24.5	10410346	320332364...	629.762500...	29.478	211.139
Maximum	6134521.473	145819.571...	19988.4320...	3652.2	334768769....	216829504...	92082.828	6611.687	21632.312
Minimum	2863.426	-16981.816	0.5	0.33	281200	5686579747...	14.2178052...	1.00816842...	18.447
Std. Dev.	912671.745...	27282.7242...	3490.16633...	777.607828...	55388691.3...	270115201...	10985.6593...	773.057314...	2877.56983...
Skewness	5.21089625...	2.14126864...	3.28529500...	2.76412271...	3.42900368...	5.05344800...	4.93488440...	4.72737291...	4.39113024...
Kurtosis	30.5915982...	7.54789690...	13.3696627...	9.20439772...	16.7683600...	31.5201816...	29.5009168...	27.5074935...	23.4535767...
Jarque-Bera	30193.1280...	1359.31830...	5249.47242...	2402.57502...	8241.56676...	31891.6620...	26523.7457...	23374.0704...	16866.8594...
Probability	0	6.72637879...	0	0	0	0	0	0	0
Sum	291710561....	15899610.6...	1156301.56...	264189.246...	284585179...	965923297...	3022136.18...	212141.656...	949072.989...
Sum Sq. Dev.	693030802...	621529778...	101713529...	504298061....	2.56170245...	6.09234553...	959443463...	485265500....	6756813032...
Observations	833	836	836	835	836	836	796	813	817

4.2. Stationarity and Co-Integration Test

Table 8: Stationarity unit root test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.407727	0.137149	46.72079	0.0000
@TREND	-0.030472	0.011180	-2.725667	0.0068

R-squared	0.023703	Mean dependent var	6.087773
Adjusted R-squared	0.020513	S.D. dependent var	1.257721
S.E. of regression	1.244755	Akaike info criterion	3.282227
Sum squared resid	474.1209	Schwarz criterion	3.306448
Log likelihood	-503.4629	Hannan-Quinn criter.	3.291912
F-statistic	7.429260	Durbin-Watson stat	0.001451
Prob(F-statistic)	0.006787		

Table 9: Stationarity ADF Test

Method	Statistic	Prob.**
ADF - Fisher Chi-square	83.2870	0.0000
ADF - Choi Z-stat	-5.52013	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results ABAT

The null hypothesis of the Augmented Dickey Fuller Test (ADF) root test using AIC selection criteria suggest that ABAT (intercept), ET (intercept and trend), PAT (intercept and trend), OP (intercept and trend) and NO (intercept and trend) are stationary. Meanwhile, the alternative hypothesis observed GDP was non-stationary at the 95% significance level.

4.3. Regression Outcomes

4.3.1. CO2

In Table 11, the year dummies have been used to correct Table 10. The corrected regression puts the model that deviated from the 5% boundaries in Figures 1 and 3. Figure 2 shows the trend that was checked for sharp changes in trend, but none warranted the Chow test.

Table 10: LM Test for Serial Correlation for LNCO2_OC

Dependent Variable: LNCO2_OC
Method: Least Squares
Date: 03/29/22 Time: 14:50
Sample: 2000 2021
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET_OC	3.47E-07	1.36E-06	0.255879	0.8015
PAT_OC	0.000386	0.000180	2.140780	0.0491
ABAT_OC	0.000590	0.000513	1.148348	0.2688
LNOP_OC	0.247784	0.172846	1.433551	0.1722
GDP_OC	-2.03E-14	3.01E-14	-0.674330	0.5104
LNCO_OC	-0.074276	0.058271	-1.274658	0.2218
C	9.173289	3.319741	2.763254	0.0145

R-squared	0.929411	Mean dependent var	12.88965
Adjusted R-squared	0.901176	S.D. dependent var	0.055004
S.E. of regression	0.017291	Akaike info criterion	-5.023874
Sum squared resid	0.004485	Schwarz criterion	-4.676724
Log likelihood	62.26261	Hannan-Quinn criter.	-4.942095
F-statistic	32.91650	Durbin-Watson stat	1.255004
Prob(F-statistic)	0.000000		

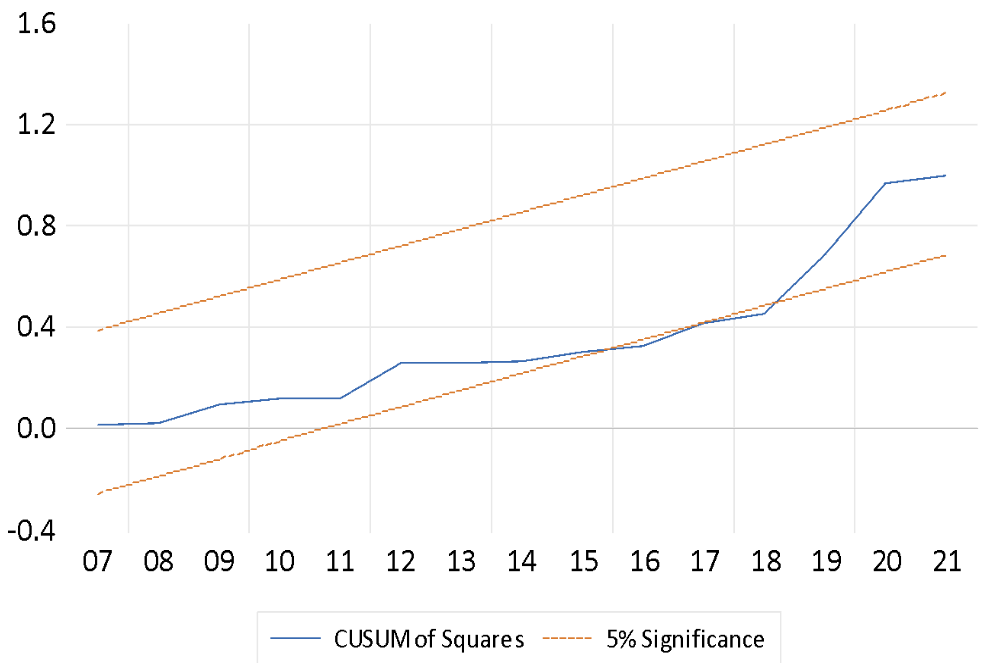

Fig.1: LNNO_OC CUSUM of squares without corrections

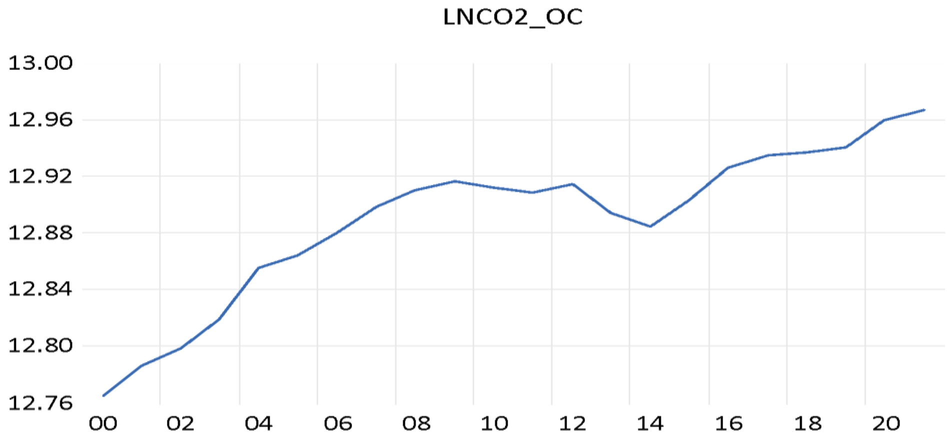

Fig.2: Graph showing the trend line of LNCO2_OC

The data suggests that 90% of independent variables account for the variation in the dependent variable, R-squared adjusted. Autocorrelation is then demonstrated by the Durbin-Watson statistic (1.250302), which lies within the range 0–1.5.

Table 11: LNCO2_OC corrected panel data regression

Dependent Variable: LNCO2_OC
Method: Least Squares
Date: 03/29/22 Time: 15:52
Sample: 2000 2021
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET_OC	3.53E-07	1.39E-06	0.253725	0.8034
PAT_OC	0.000383	0.000185	2.068925	0.0575
ABAT_OC	0.000601	0.000528	1.139775	0.2735
LNOP_OC	0.268222	0.182223	1.471942	0.1632
GDP_OC	-1.93E-14	3.10E-14	-0.622023	0.5439
LNCO_OC	-0.061877	0.064928	-0.952996	0.3568
Y1-Y22	-0.007940	0.016188	-0.490498	0.6314
C	8.726721	3.526652	2.474506	0.0268

R-squared	0.930604	Mean dependent var	12.88965
Adjusted R-squared	0.895906	S.D. dependent var	0.055004
S.E. of regression	0.017746	Akaike info criterion	-4.950003
Sum squared resid	0.004409	Schwarz criterion	-4.553261
Log likelihood	62.45004	Hannan-Quinn criter.	-4.856543
F-statistic	26.82010	Durbin-Watson stat	1.250302
Prob(F-statistic)	0.000000		

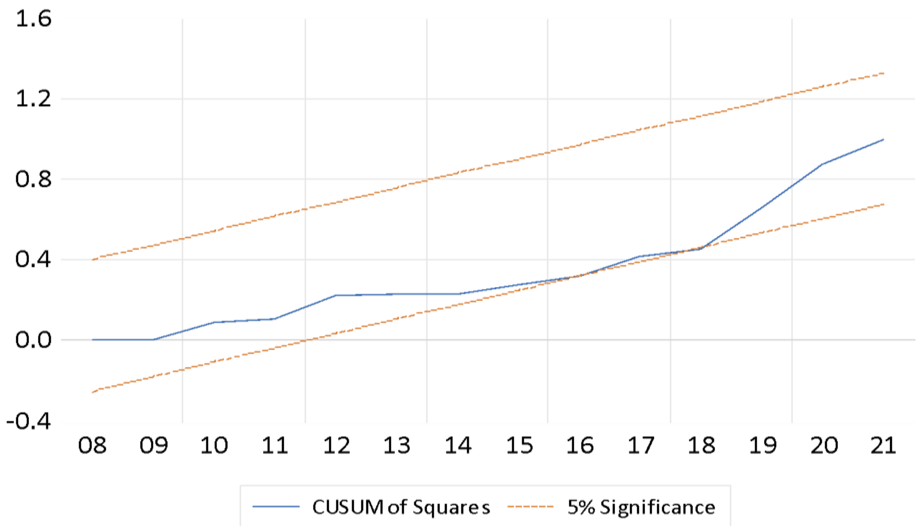

Fig.3: Corrected model CUSUM of squares

4.3.2. NO

Table 12 displays the preliminary panel data regression used to validate the panel models. The p-value for LNOP OC being greater than 0.05 indicates that it adequately explains the LNNO OC, while the other variables do not. Because the independent variables collectively explain 96.5 percent of the dependent variable, the model is suitable, as indicated by the R-squared value (0.965298). The model fits the data very well; the adjusted R-squared value is 0.954453. Positive autocorrelation is indicated by the Durbin-Watson statistic (0.835774) being less than 1.5.

Table 12: Regression of the panel data for LNNO_OC

Dependent Variable: LNNO_OC
Method: Least Squares
Date: 03/29/22 Time: 13:40
Sample: 2000 2021
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET_OC	1.83E-06	1.92E-06	0.951071	0.3557
PAT_OC	0.000223	0.000227	0.983033	0.3402
ABAT_OC	-0.000496	0.000727	-0.682206	0.5049
LNOP_OC	1.018117	0.150069	6.784335	0.0000
GDP_OC	-2.77E-14	4.25E-14	-0.651191	0.5242
C	-9.518180	2.502154	-3.803995	0.0016

R-squared	0.965298	Mean dependent var	7.765221
Adjusted R-squared	0.954453	S.D. dependent var	0.114891
S.E. of regression	0.024520	Akaike info criterion	-4.351687
Sum squared resid	0.009619	Schwarz criterion	-4.054130
Log likelihood	53.86856	Hannan-Quinn criter.	-4.281592
F-statistic	89.01308	Durbin-Watson stat	0.835774
Prob(F-statistic)	0.000000		

Recursive estimates indicate that the model was stable and did not have any breaks, since the 5% boundary was still not crossed. This is shown in Figure 4. In this case, it was not necessary to use the chow test to check for breaks.

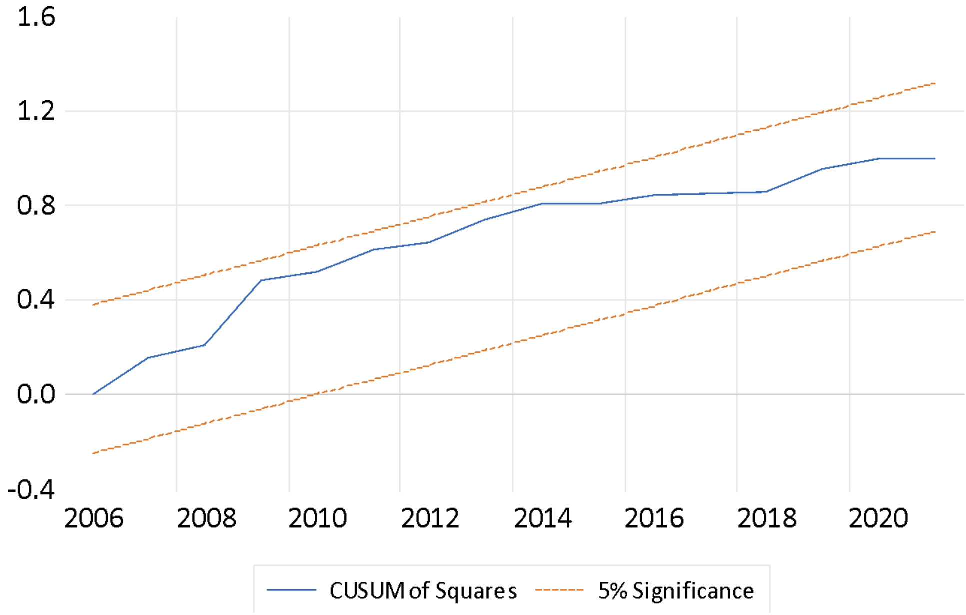

Fig.4: Recursive estimates for LNNO_OC

5. CONCLUSIONS

The study revealed that CO_2 had a statistically significant correlation with the independent variables. The short-term effects of environmental taxes on reducing emissions were clear. However, the outcome was much smaller long-term, suggesting that the current taxes are not effective with the exception of controlling CO_2 emissions. Global cooperation will be necessary. The study ultimately suggests small changes can eventually amount to large impacts, particularly regarding energy use. This research further revealed that economic development can predict the CO_2 emission in a short and long period of time. Further technological advancements directly affect the level of pollution from PM2.5 and NO, a problem which may be regulated by a green tax.. Just a 1% increase in taxation can cause emissions to decrease significantly within the short-term (0.055%) and even more dramatically in the long-term (0.063%).

OECD member countries have been able to reduce their NO_2, CO_2, and PM2.5 emissions in the short term via slight changes to environmental tax rates and policies. Changes in behavior can have short-term impacts, for example, while long-term results can be achieved through greater chance, typically economic in nature. The results can assist in moving forward with incremental changes and green taxes.

Analysis of evidence suggests that environmental taxes in OECD countries with relatively low air pollution emissions are effective in reducing such emissions over the short term, with a significance level of $p=0.05$, but will have less impact on nations with high or moderate levels of air pollution. A 1% increase in such taxes results in reductions as high as 0.0371%, 0.0314%, and 0.0251% for countries with low, medium, and higher abatement & taxation incentives, respectively. This was found true, however, only with CO_2 and NO. Though technology may one day assist, green taxes are currently the most efficient way to stem emissions. A such, an increase in air pollutants is inversely correlated with environmental taxes. Environmental taxes do not have a long-term impact in the OECD due to technological and financial incentives.

Since this research shows that technology and taxes have a significant effect on CO_2, NO, and PM25, governments should tax organizations with high emission rates, decreasing use of nonrenewable resources, including use of fossil fuels which will decrease air pollution. Other techniques, such as patenting air pollution technology, may also be useful. Tax laws can be changed to meet these needs. Governments, however, must be careful in how they spend their money and the initiatives they begin, assessing their infrastructure to ensure they can accommodate such changes.

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APPENDIX

Table 1: LNNO_OC Endogeneity Testing

Dependent Variable: LNNO_OC
Method: Panel Least Squares
Date: 03/29/22 Time: 18:41
Sample: 2000 2021
Periods included: 22
Cross-sections included: 38
Total panel (unbalanced) observations: 816

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET_OC	3.93E-07	1.25E-06	0.313744	0.7538
PAT_OC	2.55E-05	8.96E-06	2.849771	0.0045
ABAT_OC	-0.000106	6.33E-05	-1.674183	0.0945
LNOP_OC	0.261030	0.108635	2.402813	0.0165
GDP_OC	-2.98E-14	1.12E-14	-2.652874	0.0081
C	1.436125	1.781366	0.806193	0.4204

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.993017	Mean dependent var	5.698578
Adjusted R-squared	0.992432	S.D. dependent var	1.548733
S.E. of regression	0.134729	Akaike info criterion	-1.095917
Sum squared resid	13.65024	Schwarz criterion	-0.726944
Log likelihood	511.1343	Hannan-Quinn criter.	-0.954307
F-statistic	1697.479	Durbin-Watson stat	0.177734
Prob(F-statistic)	0.000000		

Table 2: LNNO_OC Wald Test for Equation Endogeneity

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	11.89840	810	0.0000
F-statistic	141.5718	(1, 810)	0.0000
Chi-square	141.5718	1	0.0000

Null Hypothesis: C(1)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	4.47E-05	3.76E-06

Restrictions are linear in coefficients.

Table 3: LNCO2_OC Endogeneity

Dependent Variable: LNCO2_OC
Method: Panel Least Squares
Date: 03/29/22 Time: 19:13
Sample: 2000 2021
Periods included: 22
Cross-sections included: 38
Total panel (unbalanced) observations: 795

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET_OC	-7.17E-07	9.95E-07	-0.720363	0.4715
PAT_OC	2.99E-05	7.10E-06	4.216369	0.0000
ABAT_OC	-5.70E-05	5.02E-05	-1.136528	0.2561
LNOP_OC	0.859089	0.089079	9.644164	0.0000
GDP_OC	-3.07E-14	8.88E-15	-3.449937	0.0006
LNCO_OC	-0.014126	0.021176	-0.667074	0.5049
C	-2.451921	1.495309	-1.639742	0.1015

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.995883	Mean dependent var	11.51209
Adjusted R-squared	0.995522	S.D. dependent var	1.592730
S.E. of regression	0.106582	Akaike info criterion	-1.561589
Sum squared resid	8.292521	Schwarz criterion	-1.179083
Log likelihood	685.7317	Hannan-Quinn criter.	-1.414604
F-statistic	2759.113	Durbin-Watson stat	0.200191
Prob(F-statistic)	0.000000		

Table 4: LNCO2_OC Wald Test

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	-0.720363	730	0.4715
F-statistic	0.518923	(1, 730)	0.4715
Chi-square	0.518923	1	0.4713

Null Hypothesis: C(1)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	-7.17E-07	9.95E-07

Restrictions are linear in coefficients.

Table 5: Stationarity unit root test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.407727	0.137149	46.72079	0.0000
@TREND	-0.030472	0.011180	-2.725667	0.0068

R-squared	0.023703	Mean dependent var	6.087773
Adjusted R-squared	0.020513	S.D. dependent var	1.257721
S.E. of regression	1.244755	Akaike info criterion	3.282227
Sum squared resid	474.1209	Schwarz criterion	3.306448
Log likelihood	-503.4629	Hannan-Quinn criter.	3.291912
F-statistic	7.429260	Durbin-Watson stat	0.001451
Prob(F-statistic)	0.006787		

Table 6: Testing Cointegration

Johansen Fisher Panel Cointegration Test
Series: LNNO PAT LNOP GDP ET ABAT
Date: 11/18/21 Time: 08:53
Sample: 2000 2021
Included observations: 308
Trend assumption: Linear deterministic trend
Lags interval (in first differences): 1 1

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	641.0	0.0000	334.9	0.0000
At most 1	391.8	0.0000	233.3	0.0000
At most 2	205.3	0.0000	107.6	0.0000
At most 3	120.5	0.0000	67.52	0.0000
At most 4	81.63	0.0000	55.95	0.0013
At most 5	74.14	0.0000	74.14	0.0000

* Probabilities are computed using asymptotic Chi-square distribution.

Table 7: Dubin-Watson test for original variables

Dependent Variable: LNNO
Method: Least Squares
Date: 11/18/21 Time: 10:16
Sample: 1 308
Included observations: 308

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-14.52612	0.956990	-15.17898	0.0000
PAT	-1.17E-05	2.22E-05	-0.526278	0.5991
LNOP	1.258836	0.061319	20.52942	0.0000
GDP	8.21E-14	1.31E-13	0.627844	0.5306
ET	-1.76E-05	5.64E-06	-3.124414	0.0020
ABAT	-5.24E-05	0.000124	-0.422538	0.6729

R-squared	0.780456	Mean dependent var	6.087773
Adjusted R-squared	0.776822	S.D. dependent var	1.257721
S.E. of regression	0.594170	Akaike info criterion	1.815985
Sum squared resid	106.6174	Schwarz criterion	1.888649
Log likelihood	-273.6617	Hannan-Quinn criter.	1.845039
F-statistic	214.7162	Durbin-Watson stat	0.091049
Prob(F-statistic)	0.000000		

Table 8: Removal of heteroscedasticity results

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.512607	Prob. F(6,804)	0.1709
Obs*R-squared	9.052475	Prob. Chi-Square(6)	0.1706
Scaled explained SS	238.7220	Prob. Chi-Square(6)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/29/22 Time: 21:26
Sample: 2 836
Included observations: 811

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.524982	0.587923	0.892943	0.3722
LNNO_OC(-1)	-0.064797	0.032793	-1.975929	0.0485
ET_OC(-1)	6.29E-06	3.71E-06	1.694005	0.0907
PAT_OC(-1)	3.49E-05	2.49E-05	1.399191	0.1621
ABAT_OC	-0.000281	0.000117	-2.392537	0.0170
LNOP_OC(-1)	-0.004892	0.036609	-0.133637	0.8937
GDP_OC(-1)	-9.85E-15	2.92E-14	-0.337575	0.7358

R-squared	0.011162	Mean dependent var	0.143878
Adjusted R-squared	0.003783	S.D. dependent var	1.054641
S.E. of regression	1.052645	Akaike info criterion	2.949082
Sum squared resid	890.8809	Schwarz criterion	2.989635
Log likelihood	-1188.853	Hannan-Quinn criter.	2.964651
F-statistic	1.512607	Durbin-Watson stat	2.008049
Prob(F-statistic)	0.170940		