Investigating the Relationship Between Canada’s Environmental Quality and GDP-Alternative Measures: An Error Correction Approach

**Sochi Iwuoha[[1]](#footnote-1), Joseph I. Onochie[[2]](#footnote-2)**

**Abstract**

This paper investigates the long-run relationship between Canada’s total greenhouse gas emissions (as an indicator of environmental quality) and economic development captured by gross domestic product (GDP) and GDP-alternative measures (which are argued to be more representative of the wider-scale economic progress, Rani & Mandal, 2020). The three GDP-alternative measures assessed were gross national disposable income (GNDI), human development index (HDI), and index of economic freedom (IEF). Time series properties of per capita greenhouse gas emissions (GHGpc) were evaluated. Augmented Dickey Fuller stationarity test was performed for GHGpc, after which, Johansen tests were performed to evaluate cointegration between GHGpc and the economic growth measures. Error correction models were run to evaluate the long-run behavior of GHGpc with per capita GDP and GNDI (GDPpc and GNDIpc, respectively), HDI, and IEF. GHGpc was found to be cointegrated with both GDPpc and all the GDP-alternative indicators. The paper contributes to the existing literature by demonstrating that Canada’s per capita GHG emission has a long-run relationship with both GDP and GDP-alternative indicators. This study represents the first assessment in the body of knowledge of the relationship between Canada’s national-level total GHG emissions and GDP-alternative measures.

**JEL classification numbers:** xxxxx

**Keywords:** Greenhouse gas, stationarity, cointegration, error correction, GDP-alternatives

1. Introduction

Canada has established regulatory frameworks to assist the country in achieving its intended nationally-determined contribution (INDC) targets to reduce greenhouse gas (GHG) emissions in line with the United Nations Framework Convention on Climate Change (UNFCCC) Paris Climate accord (Doluweera et al., 2018; Gao et al., 2017; Iwuoha, 2018; Millington et al., 2020; and Umeozor et al., 2019).

Successful policy formulation and implementation is, however, dependent on a robust understanding of the environment, economic performance, and development metrics by which the progress towards achieving the INDC targets can be measured and monitored. Historically in Canada, where efforts have been made to understand the environment-growth nexus, the methods applied have primarily relied on the use of gross domestic product (GDP) as the economic growth metric and carbon dioxide (CO2) as the measure of environmental quality (Destek et al., 2020; Government of Canada, 2020c; Guo et al., 2017; Hosseini et al., 2019; Okumuş & Bozkurt, 2020; and Schandl et al., 2016).

As a result of the above-mentioned historical approaches used in Canada, two major gaps exist in the literature:

(a) The role of Canada’s overall economic progress in achieving the INDC is poorly understood. This is because, GDP itself has been debated to be limited in capturing wholescale economic wellbeing (Ivkovic, 2016; and Whitby et al., 2014). It has been argued that the overall wellbeing of a nation will be crucial in achieving GHG emission reduction targets, given the interconnected nature of today’s world and the impact that socio-economic progress can have on the options and societal choices that can ultimately lead to emissions reduction (Seto et al., 2016).

(b) There is a lack of clarity on the link between total GHG emissions and Canada’s economic progress. We opine that since the ultimate objective is to reduce the total GHG emissions, it is paramount that effort is directed towards understanding the environment-growth nexus by using the total GHG emissions as an indicator of environmental quality, rather than mostly relying on the perspectives gained from studying components of Canada’s emissions profile such as CO2 (Huisingh et al., 2015; Shahbaz et al., 2013; and Tan et al., 2017).

Efforts at addressing the gaps identified above in Canada are still limited in the literature, hence our developing this paper that researches the relationship between the total GHG emissions and GDP-alternative measures.

* 1. Purpose of the Study

The objectives of this study, therefore, are to (a) establish the relationship between Canada’s per capita total GHG emissions (GHGpc) and economic development (captured by GDP-alternative measures) and (b) investigate if a long-run relationship exists between Canada’s GHGpc and economic development.

Given the ubiquitous use of GDP as an economic growth metric, this study also incorporates an analysis of GDP for comparison, for both objectives (a) and (b) above.

1. Brief Review of the Literature

Since the Kyoto Protocol in 1997 and the subsequent Paris climate accord in 2015, many Organization for Economic Co-operation and Development (OECD) countries (which includes Canada) have voluntarily set targets to improve their environmental performance (through GHG emissions reduction) and attract broad attention toward establishing and developing alternative sources of energy (Falkner, 2016; Gao et al., 2017; Grubb et al., 2018; Horowitz, 2016; Iwata & Okada, 2014; Maamoun, 2019; Obergassel et al., 2015; Victor, 2011; and Yang et al., 2017).

Since 2002, investment in sustainable sources of energy in OECD countries has represented at least $1 trillion USD, and, sustainable energy supply grew on average by three percent annually between 1971 and 2014, relative to one percent per year for total primary energy supply (Guo et al., 2017).

As was indicated in Section 1, CO2 emissions have been historically primarily used in the environment-growth nexus literature as a leading indicator of environmental performance (Abbasi & Riaz, 2016; Al-mulali & Binti Che Sab, 2012; Bekhet et al., 2017; and Bekun et al., 2019). Although CO2 emissions constitute the largest proportion of GHG emissions (Figures 1 and 2), emissions time series data, however, show that the trends in CO2 emissions may not necessarily be representative of (and can differ from) the aggregate GHG emissions trend (Figure 3).

Furthermore, with natural gas being considered a bridge fuel in the transition towards a lower-carbon economy and methane (CH4) being the primary constituent of natural gas (Howarth et al., 2011), the importance of capturing a fuller picture of the total GHG emissions in environment-growth studies cannot be overstated, particularly given that CH4 contributes the second-highest proportion of GHG emissions (Figures 1, 2, 3, and 4; Whittenberg, 2021).

The total GHG emissions has, indeed, been used in OECD and other countries to evaluate the relationship between environmental quality and economic performance, however, its use in Canada is limited (Blindheim, 2015; Hoyle, 2020; Iwata & Okada, 2014; Jordaan et al., 2017; and Maaloul, 2018).

Chart, diagram

Description automatically generated

Figure 1: 2015 Global GHG emissions share by gas

*Source*: US EPA (2016)

*Note*: Total (or aggregate) GHG emissions is comprised of CO2, CH4, Nitrous oxide (N2O), and Fluorinated gases or F-gases (nitrogen trifluoride, hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride.

Chart, pie chart

Description automatically generated

Figure 2: Canada’s 2016 GHG emissions share by gas

*Data Source*: Ritchie & Roser, 2017.

*Note*: Canada’s Aggregate GHG emission was ~779 megatonnes (Mt) CO2 equivalent (CO2e) (Ritchie & Roser, 2017).

Figure 3: Canada’s per capita GHG emissions by gas from 1990 to 2016

*Note*: Data from (Ritchie & Roser, 2017).



Figure 4: 2016 Global GHG emissions by sector, end-use, and gas (Ge & Friedrich, 2020).

One of the challenges with conducting environment-growth research using aggregate GHG emissions for some countries is the difficulty of data collection and aggregation for the constituent gases (CO2, CH4, nitrous oxide - N2O, and fluorinated gases) thereby leading to elevated levels of uncertainty on the total GHG emissions estimate for some countries (Masnadi et al., 2018). Being a subscriber to both the Paris climate accord and the predecessor Kyoto Protocol, Canada has historically reported its GHG emissions data for several decades and the reported numbers are reviewed for consistency with the UNFCCC-prescribed GHG accounting methods (Government of Canada, 2020a, 2020b; Ritchie & Roser, 2017). It has been argued that Canada’s regulatory standards and enforcement policies facilitate a high level of reporting transparency and has over the years helped in reducing the level of uncertainty in the Canada’s GHG emissions data capturing and reporting, relative to other countries (Figure 5; Blair, 2021; Ritchie & Roser, 2017). This, therefore, implies that the Canada’s GHG emissions data can be considered sufficiently representative to be used to evaluate the relationship between GHG emission and economic development.



Figure 5: Data quality scores of volume-weighted-average crude oil production GHG intensity estimates

*Source*: Masnadi et al. (2018)

*Note*: The reference year is 2015 and the number below a country name represents the number of fields studied. On the data quality color legend, the number 10 is the highest data quality score while 0 marks the lowest score. The author only plotted countries whose oil production share is ≥ 0.1% of the global production. The figure shows a high data quality score for the 84 Canadian fields analyzed.

The use of GDP-alternative indicators in empirical environment-growth nexus studies is an area of developing research with little traction gained over the past ten years. Although efforts have been made both in the global and Canadian literature to evaluate the role of determinants such as trade, energy consumption, foreign direct investment (FDI) in the environment-growth nexus (Ben Jebli et al., 2016; Camarero et al., 2015; Dogan, 2016; Farhani & Shahbaz, 2014; Jayanthakumaran & Liu, 2012; Singhania & Saini, 2021), the body of knowledge on the relationship between other “alternative” indicators of economic progress or well-being and environmental quality remains limited.

IEF has been utilized across European, Middle East, and African countries using CO2 as the pollutant (Cobb et al., 1995; IMF, 2011; Ivkovic, 2016; Kimmerer, 2020; McGregor, 2003; and Rani & Mandal, 2020). In Canada, however, there has been little to no traction on using GDP-alternative measures to evaluate the relationship between environmental quality and economic development. No assessment to date exists that evaluates the long run relationship between Canada’s national-level GHGpc and any GDP-alternative indicator. As a result, there is a poor understanding of how Canada’s wholescale economic development can support or impede the nation’s objectives of achieving INDC targets to reduce aggregate GHG emissions.

By evaluating in this research, a set of wider-scale measures of economic performance (through the GDP-alternative indicators), the role of the externalities not captured by GDP are incorporated to provide complementary insight on the relationship between Canada’s environmental performance and wholescale economic progress (Kneese et al., 2015; Victor, 2017; and Victor & Dolter, 2017).

1. Data and Methodology

The research data for GDP, GNDI, HDI, IEF, and population (which was used to calculate GDPpc, GNDIpc, and GHGpc) were obtained from the same sources as Iwuoha & Onochie (2022), i.e., the databases for the OECD, United Nations Development Programme (UNDP), and Heritage Foundation. GHG data was retrieved from the United Nations (UN) 2020 Common Reporting Format Table (Government of Canada, 2020a). The time series period evaluated in this assessment is from 1995 – 2019.

Time series plots of GHGpc were generated to visually assess the behavior and trend of GHGpc during the period evaluated. Paired time series plots of GHGpc with GDP and the GDP-alternative measures (i.e., GNDIpc, HDI, and IEF) were also created to comparatively view the trend of GHGpc with the growth indicator trends. The descriptive statistics of the GHGpc time series were calculated, including the quantiles and measures of symmetry. Note that Iwuoha & Onochie (2022) reported the descriptive statistics of the GDPpc, GNDIpc, HDI, and IEF time series.

Augmented Dickey-Fuller (ADF) test was performed to assess the stationarity of the level and first difference of GHGpc. The stationarity of the variable was determined by considering the asymptotic p-values of the ADF test. GDPpc, GNDIpc, HDI, and IEF were already confirmed though ADF testing to be stationary at first difference (Iwuoha & Onochie, 2022).

Furthermore, Johansen cointegration (JC) tests were performed to evaluate if GHGpc is cointegrated with GDPpc, GNDIpc, HDI, and IEF, respectively. Error correction models were run to evaluate the long-run behavior of GHGpc with GDPpc and the GDP-alternative growth measures. The cointegration and error correction methods applied in this study have been previously applied in the literature to evaluate the environment-growth relationship in both OECD countries and other nations (Apergis & Payne, 2014).

Where a cointegrated relationship is confirmed to exist between two variables, the relationship can be written as an error correction model expressed as (Enns et al., 2016):

ΔYt = α0 + α1Yt-1 + β0ΔXt + β1Xt-1 + ℇt (Equation 1)

where ΔYt is the change in the dependent variable, α0 is a constant (or the intercept), α1 is the error correction rate, Yt-1 is the dependent variable lagged by one period, β0 is the coefficient of the change in the explanatory variable, ΔXt is the change in the explanatory (or independent) variable, β1 is the coefficient of the lagged value of the explanatory variable, Xt-1 is the explanatory variable lagged by one period, and ℇt is the error term (or the residual).

Single-equation ordinary least squares (OLS)-based ECMs were set up to test for the existence of a long run relationship between GHGpc and each of the GDP-alternative measures, as well as “weak exogeneity” in GHGpc (Urbain, 2012). Heteroskedasticity and autocorrelation consistent (HAC) standard error estimation was applied when generating the ECMs.

Post-ECM model specification tests were performed (a) to assess the characteristics and quality of the ECMs and (b) to select the reference ECM scenarios considered to be representative for capturing the long run relationship between GHGpc and each of the growth measures. Six specification tests were performed on the ECMs and the p-values were used to determine whether to reject or fail to reject the null hypotheses of the specification tests. The ECM results reported in this paper are for the selected reference scenarios that passed the post-ECM specification tests.

1. Results and Discussion

Figures 6A and 6B show the GHGpc time series plots by level and first difference while Figures 7A to 7D show the overlay plots by level of the GHGpc time series with each of the GDP-alternative indicators. GHGpc descriptive statistics are reported in Table 1. Table 2 contains the results from the tests for stationarity for GHGpc from the ADF analysis.

The results from the vector auto-regression (VAR) lag selection used for JC testing for GHGpc and each of the GDP-alternative measures are presented in Table 3. Tables 4 to 11 report the JC test results for GHGpc paired with the GDP-alternative indicators. These results are for the “unrestricted constant” and “unrestricted constant and trend” scenarios which were selected as the reference scenarios for reporting based on the visually observed trend of the time series plots (Figures 7A to 7D). The JC testing summary results for all the scenarios tested are shown in Table 12 which also highlights the reference scenarios used for the ECM assessments. The number of cointegrated scenarios for the JC testing are indicated in Table 13.

ECM results are presented in Tables 14 to 17 with the outcomes of post-ECM specification tests reported in Table 18 and Figure 8. A summary of the assessment of exogeneity of GHGpc from the ECM is shown in Table 19.



Figure 6: GHGpc time series plots by level and first difference (growth level)

*Note*: (a) The time series plot of GDP and the GDP-alternative measures is shown in Figure 2 below, paired with GHGpc. (b) The first difference of GDP and the GDP-alternative measures is reported in Iwuoha & Onochie (2022).



Chart, line chart

Description automatically generated

Figure 7: Paired time-series plots (by level) of GHGpc and GDP-Alternative measures

Table 1: Summary statistics, quantiles, and measures of symmetry of Canada’s GHGpc

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Mean | Median | Min. | Max. | Std. Dev. | Variance | C.V. |
| 21.37 | 21.49 | 19.60 | 23.49 | 1.2493 | 1.5610 | 0.058 |
|  |  |  |  |  |  |  |
| 5% Perc. | 95% Perc. | IQ range | Skewness | Skewness Comment | Excess kurtosis | Kurtosis Comment |
| 19.61 | 23.41 | 2.12 | 0.09 | Positive fairly symmetrical | -1.3210 | Platykurtic |

*Note*: (a) C.V. is the coefficient of variation. (b) Variance is in squared units (c) The summary statistics of GDP, GNDI, HDI, and IEF are reported and discussed in Iwuoha & Onochie (2022).

Table 2: Summary results of ADF unit root tests for GHGpc

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Type | p-value | Stationarity |
| GHGpc | Level | 0.5246 | Non-stationary |
| First difference | 0.9821 | Non-stationary |
| First difference\* | 0.0896 | Stationary at the 10% level but not at the 1% and 5% significance levels |

*Note*: (a) Unless otherwise indicated, the ADF results were derived from tests that were performed using the “constant and trend” scenario. (b) \*refers to a test with constant only. (c) The ADF unit root test results of GDP, GNDI, HDI, and IEF are reported and discussed in Iwuoha & Onochie (2022). The results indicated that GDP, GNDI, HDI, and IEF are non-stationary at level and stationary when first-differenced.

Table 3: Summary of VAR lag selection results for GHGpc and GDP-Alternatives paired cointegration testing

|  |  |  |
| --- | --- | --- |
| Variables | Scenario | Lag Length |
| GHGpc vs GDPpc | With constant | 7 |
| With constant and trend | 7 |
| GHGpc vs GNDIpc | With constant | 7 |
| With constant and trend | 7 |
| GHGpc vs HDI | With constant | 7 |
| With constant and trend | 7 |
| With constant and trend | 7 |
| GHGpc vs IEF | With constant | 7 |
| With constant and trend | 7 |

*Note:* The reported lag length was selected based on the Akaike Information Criterion (AIC).

Table 4: JC test results for GHGpc and GDPpc with unrestricted constant

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.9787 | 87.068 | [0.0000] | 69.287 | [0.0000] |
| 1 | 0.62762 | 17.781 | [0.0000] | 17.781 | [0.0000] |

*Note:* (a) The JC test was run with a lag length of 7 obtained from the paired VAR lag selection (Table 3). (b) Lmax is the Lambda max test. This note applies to all the other paired cointegration tests subsequently reported in Tables 5 to 11.

Table 5: JC test results for GHGpc and GDPpc with unrestricted constant and trend

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.94341 | 59.441 | [0.0000] | 51.694 | [0.0000] |
| 1 | 0.34976 | 7.7475 | [0.0054] | 7.7475 | [0.0054] |

Table 6: JC test results for GHGpc and GNDIpc with unrestricted constant

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.98731 | 93.629 | [0.0000] | 78.601 | [0.0000] |
| 1 | 0.56607 | 15.028 | [0.0001] | 15.028 | [0.0001] |

Table 7: JC test results for GHGpc and GNDIpc with unrestricted constant and trend

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.9747 | 74.648 | [0.0000] | 66.186 | [0.0000] |
| 1 | 0.37508 | 8.4623 | [0.0036] | 8.4623 | [0.0036] |

Table 8: JC test results for GHGpc and HDI with unrestricted constant

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.922530 | 47.515 | [0.0000] | 46.041 | [0.0000] |
| 1 | 0.078585 | 1.4732 | [0.2248] | 1.4732 | [0.2248] |

Table 9: JC test results for GHGpc and HDI with unrestricted constant and trend

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.974470 | 73.247 | [0.0000] | 66.023 | [0.0000] |
| 1 | 0.330560 | 7.2236 | [0.0072] | 7.2236 | [0.0072] |

Table 10: JC test results for GHGpc and IEF with unrestricted constant

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.968580 | 109.850 | [0.0000] | 62.28700 | [0.0000] |
| 1 | 0.928810 | 47.562 | [0.0000] | 47.56200 | [0.0000] |

Table 11: JC test results for GHGpc and IEF with unrestricted constant and trend

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Eigenvalue | Trace Test | p-value (Trace) | Lmax Test | p-value (Lmax) |
| 0 | 0.991410 | 126.470 | [0.0000] | 85.63100 | [0.0000] |
| 1 | 0.896580 | 40.841 | [0.0000] | 40.84100 | [0.0000] |

Table 12: Summary of JC testing for GHGpc paired with GDP and GDP-Alternative measures

|  |  |  |
| --- | --- | --- |
| Variables | Scenario | Cointegrated? |
| GHGpc vs GDPpc | No constant | No |
| Restricted constant | Yes |
| Unrestricted constant\* | Yes |
| Restricted trend | Yes |
| Unrestricted trend | Yes |
| GHGpc vs GNDIpc | No constant | No |
| Restricted constant | Yes |
| Unrestricted constant\* | Yes |
| Restricted trend | Yes |
| Unrestricted trend | Yes |
| GHGpc vs HDI | No constant | No |
| Restricted constant | Yes |
| Unrestricted constant | No |
| Restricted trend | No |
| Unrestricted trend\* | Yes |
| GHGpc vs IEF | No constant | Yes |
| Restricted constant | Yes |
| Unrestricted constant | Yes |
| Restricted trend\* | Yes |
| Unrestricted trend | Yes |

*Note:* (a) The maximum number of cointegrating vectors is given by n-1 where n is the number of variables tested. (b) The “Restricted trend” scenario corresponds to a test with a restricted trend and an unrestricted constant. (c) The “Unrestricted trend” scenario corresponds to a test with an unrestricted trend and an unrestricted constant. (d) \*Reference scenario for the error correction model. The selected reference scenario was confirmed to have satisfied post-ECM model specification tests (discussions are provided in the ECM and post-ECM Section 4.5).

Table 13: Number of JC testing cointegrated scenarios for GHGpc paired with GDP and GDP-Alternative measures

|  |  |
| --- | --- |
| Variables | Number of Scenarios with Cointegrated Relationships |
| GHGpc vs GDPpc | 4 |
| GHGpc vs GNDIpc | 4 |
| GHGpc vs HDI | 2 |
| GHGpc vs IEF | 5 |

*Note:* This summary table was derived from Table 12 above.

**Table 14: ECM result for GHGpc and GDPpc**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. error | t-ratio | p-value | Significance level |
| d\_GDPpc\_1 | −4.60906e-05 | 5.87100e-05 | −0.7851 | 0.4416 |  |
| e\_GHGGDP\_1 | −0.313417 | 0.122655 | −2.5550 | 0.0189 | \*\* |
| d\_GHGpc\_1 | 0.066600 | 0.195037 | 0.3415 | 0.7363 |  |

Note: (a) d\_GDPpc\_1 is the lagged difference term of the independent variable. (b) e\_GHGGDP\_1 is the lagged residual of the ECM. (c) d\_GHGpc\_1 is the lagged difference term of the dependent variable. (d) Std. error is the standard error. (e) \*\* denotes significance at the 5% level. Notes (a), (b), and (c) apply to all the other ECM results in Tables 15 to 17.

**Table 15: ECM result for GHGpc and GNDIpc**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. error | t-ratio | p-value | Significance level |
| d\_GNDIpc\_1 | −4.97610e-05 | 0.000057 | −0.8688 | 0.3952 |  |
| e\_GHGGNDI\_1 | −0.309349 | 0.120827 | −2.5600 | 0.0187 | \*\* |
| d\_GHGpc\_1 | 0.068052 | 0.194071 | 0.3507 | 0.7295 |  |

**Table 16: ECM result for GHGpc and HDI**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. error | t-ratio | p-value | Significance level |
| d\_HDI\_1 | 14.4628000 | 30.350300 | 0.47650 | 0.638900 |  |
| e\_GHGHDI\_1 | −0.363472 | 0.130298 | −2.7900 | 0.011300 | \*\* |
| d\_GHGpc\_1 | 0.029391 | 0.166620 | 0.1764 | 0.861800 |  |

**Table 17: ECM result for GHGpc and IEF**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. error | t-ratio | p-value | Significance level |
| d\_IEF\_1 | 0.1012850 | 0.102661 | 0.98660 | 0.335600 |  |
| e\_GHGIEF\_1 | −0.310630 | 0.128120 | −2.4250 | 0.024900 | \*\* |
| d\_GHGpc\_1 | 0.010290 | 0.147446 | 0.0698 | 0.945100 |  |

**Table 18: ECM post-model specification test results**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Test: | Ramsey’s RESET | White’s | ARCH | Normality | Autocorrelation | CUSUM |
| *Test Objective* | *Model specification* | *Hetero-*  *skedasticity* | *ARCH effect* | *Normality of the residual* | *Serial Correlation* | *Parameter stability* |
| *Null Hypothesis:* | *The model specification is adequate* | *Homo-*  *skedasticity* | *No ARCH* | *Normally-distributed error* | *No serial correlation* | *No change in the parameters* |
| *Test statistic* | *F* | *LM* | *LM* | *Chi-Square* | *LMF* | *Harvey-Collier t* |
| GHGpc - GDPpc  p-values: | 0.951177 | 0.309151 | 0.466839 | 0.378046 | 0.985154 | 0.502591 |
| GHGpc - GNDIpc  p-values: | 0.949111 | 0.29963 | 0.455164 | 0.378388 | 0.954621 | 0.573016 |
| GHGpc - HDI  p-values: | 0.972166 | 0.0663593 | 0.442531 | 0.210868 | 0.934991 | 0.106696 |
| GHGpc - IEF  p-values: | 0.816864 | 0.264265 | 0.650143 | 0.110059 | 0.567875 | 0.253095 |

Note: (a) LM is the Lagrange multiplier test (Bertsekas, 2014). (b) LMF is an F-approximation to the likelihood-ratio form of the LM test (Doornik, 1996). (c) ARCH is Auto-Regressive Conditional Heteroskedasticity (Andrews & Guggenberger, 2014; Aue et al., 2017; and Nkoro & Uko, 2013). (d) Ramsey’s RESET test was run after Babatunde et al. (2014), Ereeş & Demi̇rel (2012), and Volkova & Plankina (2013). (e) White’s heteroskedasticity test was performed after Astivia & Zumbo (2019), Baum & Lewbel (2019), and MacKinnon (2013). (f) Normality tests were conducted after Ghasemi & Zahediasl (2012) and Mishra et al. (2019). (g) Consistent autocorrelation test results were obtained for the LMF test statistic, the alternative TR^2 statistic, and the Ljung-Box Q statistic (Gençay & Signori, 2015 and Sun, 2013). The reference test statistic reported in the table is the LMF (h) CUSUM refers to Cumulative Sum, after Alimi (2014), Lee (2020), Nchor & Adamec (2016), and Talaş et al. (2013).

Chart

Description automatically generated with medium confidence

Figure 8: CUSUM test for ECM parameter stability - Results for GHGpc versus the growth measures

**Table 19: Summary assessment of weak exogeneity in GHG per capita from the ECMs**

|  |  |
| --- | --- |
| Cointegrating Scenario | GHGpc is weakly exogenous? |
| GHGpc vs GDPpc | No |
| GHGpc vs GNDIpc | No |
| GHGpc vs HDI | No |
| GHGpc vs IEF | No |

* 1. Time Series Plots

Over the 1995 - 2019 time series period, the GHGpc level shows multiple peaks, with the maximum GHGpc of 23.5 tonnes CO2e (tCO2e) in 2004 marking the turning point in the overall GHG trend (Figure 6A). This signifies a reversal from environmental degradation to relative improvement in the environmental performance, particularly over the last ten years of the period studied. Also, in the last ten years of the study period, GHGpc growth level revolved around the equilibrium (i.e., zero) but showed greater deviations between 1995 and 2009, after which the relative improvement in environmental performance commenced (Figure 6B).

The paired time series plot of GHGpc and IEF (Figure 7D) shows the best indication of potential co-movement between GHGpc and the GDP-alternative measures (Figures 7A to 7D). JC tests were, therefore, performed to either rule-in or rule-out the existence of cointegration between GHGpc and the growth measures. Multiple scenarios (e.g., “constant”, “constant and trend”, etc.) were tested to assess the impact of the observed visual variations in the paired time series trends on the potential for cointegration between GHGpc and the growth measures.

* 1. Descriptive Statistics

Canada’s per capita mean and median GHG emissions were similar between 1995 and 2019, being 21.4 tCO2e and 21.5 tCO2e respectively (Figure 6A and Table 1). The GHGpc time series is positive, fairly symmetrical, and platykurtic.

* 1. Stationarity

Non-stationarity is the null hypothesis of the ADF unit root test. The ADF test results reported in Table 2 indicates that over the time series period studied, GHGpc is integrated of order 1, i.e., I(1), in the “constant only” scenario. The confirmation of the I(1) status allowed for cointegration testing to be performed between GHGpc paired with the growth measures.

* 1. Cointegration

Based on the AIC, the optimal lag length for cointegration testing was 7 (Table 3). The existence of a unit root is the null hypothesis of the JC test, determined using the p-value of the error term of the cointegrating regression of the unit root test. The null hypothesis is rejected for p-value < 0.05, implying that cointegration exists between the parameters being evaluated.

Cointegrating vectors were found to be dependent on the scenario evaluated. For example, as shown in Tables 4 to 7 and 9 to 11, the cointegration criterion is satisfied at rank 1 for GHGpc and the growth measures in the “unrestricted constant” and the “unrestricted constant and trend” scenarios. A cointegrating equation exists at rank 0 between GHGpc and HDI in the “unrestricted constant scenario (Table 8). For all the scenarios tested (Table 12), a minimum of two cointegrating relationships (and up to a maximum of five) were found between GHGpc and each of the growth measures (Table 13). This confirms that GHGpc has co-movement with GDPpc and shows for the first time in the literature that Canada’s GHGpc is cointegrated with GNDIpc, HDI, and IEF.

* 1. Ordinary Least Squares Error Correction Model and Tests for Post-Error Correction Model Specification and Exogeneity

The results from the ECM specification tests show that for all the selected paired “GHGpc – growth indicator” scenarios (i.e., the reference scenarios marked with an asterix “\*” in Table 12), we failed to reject the null hypothesis for all the post-model specification tests (Table 18). This indicates that for all the reported ECMs (Tables 14 to 17):

1. The ECM specification is adequate.
2. Heteroskedasticity and ARCH are not present.
3. The ECM error is normally distributed
4. There is no autocorrelation, and
5. There were no changes in the parameters. Hence, the ECMs were within the required upper and lower model limits (Figure 8).

The ECM results, therefore, provide the equations for representing the long run equilibrium relationship that exists between GHGpc and the growth measures (i.e., GDPpc, GNDIpc, HDI, and IEF), following the prior indicated confirmation of cointegration between the variables from JC testing.

To determine whether GHGpc (the dependent variable) acts as an autonomous driving force in the GHG-growth nexus (for the evaluated growth measures) or moves to restore the equilibrium with changes in the long-run equilibrium, the null hypothesis for the cointegrating relationship is that GHGpc is weakly exogenous. The p-values of the lagged residual from the ECM (Tables 14 to 17) were used to determine whether to “reject” or “fail to reject” the null hypothesis (Urbain, 2012). The null hypothesis was rejected for p-values < 0.05 implying that for these instances, GHGpc is not weakly exogenous.

The results from this research show that for each of the paired variables of GHGpc and the growth measures, GHGpc is not exogenous in the cointegrating relationship and, therefore, adjusts (i.e., mean-reverts) to restore the long run relationship between GHGpc and each of the growth measures.

1. Summary and Conclusion

This paper demonstrates for the first time in the literature that Canada’s national-level per capita GHG emission has a long-run relationship with the GDP-alternative indicators, namely per capita gross national disposable income (GNDIpc), human development index (HDI), and the index of economic freedom (IEF). GHGpc was also confirmed to be cointegrated with per capita GDP. It was observed, however, that the greatest number of cointegrating relationships (at most five) were found between GHGpc and IEF.

This paper contributes to both the Canadian and the global body of knowledge on how GDP-alternative measures can be used to gain complementary insight into the potential dynamics between economic growth and environmental performance. The observations provide a context that should extend previous studies in the quest to understand Canada’s environment-growth nexus more holistically.

The findings of the research should also facilitate a broader assessment of the potential implication of the overall economic wellbeing of a nation on its environmental quality. This consideration can inform strategic environmental and economic policy development and implementation at the national level in Canada and, by extension, other nations.

**ACKNOWLEDGEMENTS.** We would like to thank the Journal Executive Editor Voula Papageorgopoulou and the anonymous reviewers for their guidance and feedback, respectively.

References

1. Abbasi, F., & Riaz, K. (2016). CO2 emissions and financial development in an emerging economy: An augmented VAR approach. Energy Policy, 90, 102–114. https://doi.org/10.1016/j.enpol.2015.12.017
2. Alimi, R. S. (2014). ARDL Bounds Testing Approach to Cointegration: A Re-Examination of Augmented Fisher Hypothesis in an Open Economy. Asian Journal of Economic Modelling, 2(2), 103–114.
3. Al-mulali, U., & Binti Che Sab, C. N. (2012). The impact of energy consumption and CO2 emission on the economic and financial development in 19 selected countries. Renewable and Sustainable Energy Reviews, 16(7), 4365–4369. https://doi.org/10.1016/j.rser.2012.05.017
4. Andrews, D. W. K., & Guggenberger, P. (2014). A Conditional-Heteroskedasticity-Robust Confidence Interval for the Autoregressive Parameter. The Review of Economics and Statistics, 96(2), 376–381. https://doi.org/10.1162/REST\_a\_00369
5. Apergis, N., & Payne, J. E. (2014). Renewable energy, output, CO2 emissions, and fossil fuel prices in Central America: Evidence from a nonlinear panel smooth transition vector error correction model. Energy Economics, 42, 226–232. https://doi.org/10.1016/j.eneco.2014.01.003
6. Astivia, O., & Zumbo, B. (2019). Heteroskedasticity in Multiple Regression Analysis: What it is, How to Detect it and How to Solve it with Applications in R and SPSS. Practical Assessment, Research, and Evaluation, 24(1). https://doi.org/10.7275/q5xr-fr95
7. Aue, A., Horváth, L., & F. Pellatt, D. (2017). Functional Generalized Autoregressive Conditional Heteroskedasticity. Journal of Time Series Analysis, 38(1), 3–21. https://doi.org/10.1111/jtsa.12192
8. Babatunde, O. S., Oguntunde, P. E., Ogunmola, A. O., & Balogun, O. S. (2014). On the Performance of RESET and Durbin Watson Tests in Detecting Specification Error. Copyright © 2014 by Modern Scientific Press Company, Florida, USA International Journal of Modern Mathematical Sciences, 11(3), Article 3.
9. Baum, C. F., & Lewbel, A. (2019). Advice on using heteroskedasticity-based identification. The Stata Journal, 19(4), 757–767. https://doi.org/10.1177/1536867X19893614
10. Bekhet, H. A., Matar, A., & Yasmin, T. (2017). CO2 emissions, energy consumption, economic growth, and financial development in GCC countries: Dynamic simultaneous equation models. Renewable and Sustainable Energy Reviews, 70, 117–132. https://doi.org/10.1016/j.rser.2016.11.089
11. Bekun, F. V., Alola, A. A., & Sarkodie, S. A. (2019). Toward a sustainable environment: Nexus between CO2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries. Science of The Total Environment, 657, 1023–1029. https://doi.org/10.1016/j.scitotenv.2018.12.104
12. Ben Jebli, M., Ben Youssef, S., & Ozturk, I. (2016). Testing environmental Kuznets curve hypothesis: The role of renewable and non-renewable energy consumption and trade in OECD countries. Ecological Indicators, 60, 824–831. https://doi.org/10.1016/j.ecolind.2015.08.031
13. Bertsekas, D. P. (2014). Constrained Optimization and Lagrange Multiplier Methods. Academic Press.
14. Blair. (2021, January 16). The GHG intensity of the Canadian oil industry – what the scientific research actually says. A Chemist in Langley. https://achemistinlangley.net/2021/01/15/the-ghg-intensity-of-the-canadian-oil-industry-what-the-scientific-research-actually-says/
15. Blindheim, B. (2015). A missing link? The case of Norway and Sweden: Does increased renewable energy production impact domestic greenhouse gas emissions? Energy Policy, 77, 207–215. https://doi.org/10.1016/j.enpol.2014.10.019
16. Camarero, M., Forte, A., Garcia-Donato, G., Mendoza, Y., & Ordoñez, J. (2015). Variable selection in the analysis of energy consumption–growth nexus. Energy Economics, 52, 207–216. https://doi.org/10.1016/j.eneco.2015.10.012
17. Cobb, C., Halstead, T., & Rowe, J. (1995). The Genuine Progress Indicator: Summary of data and methodology. Redefining Progress. https://books.google.com/books/about/The\_Genuine\_Progress\_Indicator.html?id=-YDaPQAACAAJ
18. Destek, M. A., Shahbaz, M., Okumus, I., Hammoudeh, S., & Sinha, A. (2020). The relationship between economic growth and carbon emissions in G-7 countries: Evidence from time-varying parameters with a long history. Environmental Science and Pollution Research, 27(23), 29100–29117. https://doi.org/10.1007/s11356-020-09189-y
19. Dogan, E. (2016). Analyzing the linkage between renewable and non-renewable energy consumption and economic growth by considering structural break in time-series data. Renewable Energy, 99, 1126–1136. https://doi.org/10.1016/j.renene.2016.07.078
20. Doluweera, G., Vypovska, A., Datta, A., & Iwuoha, S. (2018). Impacts of Carbon Management Policies on Canadian Electricity Prices (No. 171). Canadian Energy Research Institute. https://ceri.ca/studies/impacts-of-carbon-management-policies-on-canadian-electricity-prices
21. Doornik, J. A. (1996). Testing Vector Error Autocorrelation and Heteroscedasticity. 23. https://www.doornik.com/research/vectest.pdf
22. Enns, P. K., Kelly, N. J., Masaki, T., & Wohlfarth, P. C. (2016). Don’t jettison the general error correction model just yet: A practical guide to avoiding spurious regression with the GECM. Research & Politics, 3(2), 2053168016643345. https://doi.org/10.1177/2053168016643345
23. Ereeş, S., & Demi̇rel, N. (2012). Omitted Variables Bias and Detection with RESET test in Regression Analysis. Anadolu University Journal of Science and Technology B - Theoretical Sciences, 2(1), Article 1.
24. Falkner, R. (2016). The Paris Agreement and the new logic of international climate politics. International Affairs, 92(5), 1107–1125. https://doi.org/10.1111/1468-2346.12708
25. Farhani, S., & Shahbaz, M. (2014). What role of renewable and non-renewable electricity consumption and output is needed to initially mitigate CO2 emissions in MENA region? Renewable and Sustainable Energy Reviews, 40, 80–90. https://doi.org/10.1016/j.rser.2014.07.170
26. Gao, Y., Gao, X., & Zhang, X. (2017). The 2°C Global Temperature Target and the Evolution of the Long-Term Goal of Addressing Climate Change—From the United Nations Framework Convention on Climate Change to the Paris Agreement. Engineering, 3(2), 272–278. https://doi.org/10.1016/J.ENG.2017.01.022
27. Ge, M., & Friedrich, J. (2020). 4 Charts Explain Greenhouse Gas Emissions by Countries and Sectors. World Resources Institute. https://www.wri.org/blog/2020/02/greenhouse-gas-emissions-by-country-sector
28. Gençay, R., & Signori, D. (2015). Multi-scale tests for serial correlation. Journal of Econometrics, 184(1), 62–80. https://doi.org/10.1016/j.jeconom.2014.08.002
29. Ghasemi, A., & Zahediasl, S. (2012). Normality Tests for Statistical Analysis: A Guide for Non-Statisticians. International Journal of Endocrinology and Metabolism, 10(2), 486–489. https://doi.org/10.5812/ijem.3505
30. Government of Canada. (2020a). GHG Emissions—Common Reporting Format (CRF) Tables. United Nations. https://unfccc.int/documents/224828
31. Government of Canada. (2020b). Greenhouse gas sources and sinks: Executive summary (p. 15) [Program results]. Environment and Climate Change, Government of Canada. https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/sources-sinks-executive-summary-2020.html
32. Government of Canada. (2020c). Canada Gazette, Part 1, Volume 154, Number 51: Clean Fuel Regulations. Public Works and Government Services, Government of Canada. http://gazette.gc.ca/rp-pr/p1/2020/2020-12-19/html/reg2-eng.html
33. Grubb, M., Vrolijk, C., & Brack, D. (2018). Kyoto Protocol (1999): A Guide and Assessment. Routledge.
34. Guo, L. ling, Qu, Y., & Tseng, M.-L. (2017). The interaction effects of environmental regulation and technological innovation on regional green growth performance. Journal of Cleaner Production, 162, 894–902. https://doi.org/10.1016/j.jclepro.2017.05.210
35. Horowitz, C. A. (2016). Paris Agreement. International Legal Materials, 55(4), 740–755.
36. Hosseini, H., Romaniuk, A., & Millington, D. (2019). Economic and Emissions Impacts of Fuel Decarbonization (No. 179). Canadian Energy Research Institute. https://ceri.ca/assets/files/Study\_179\_Full\_Report.pdf
37. Howarth, R. W., Santoro, R., & Ingraffea, A. (2011). Methane and the greenhouse-gas footprint of natural gas from shale formations. Climatic Change, 106(4), 679. https://doi.org/10.1007/s10584-011-0061-5
38. Hoyle, A. (2020). Modelling the effect of Canada’s clean fuel standard on greenhouse gas emissions [Masters Thesis (Unpublished), Simon Fraser University]. https://summit.sfu.ca/item/20518
39. Huisingh, D., Zhang, Z., Moore, J. C., Qiao, Q., & Li, Q. (2015). Recent advances in carbon emissions reduction: Policies, technologies, monitoring, assessment and modeling. Journal of Cleaner Production, 103, 1–12. https://doi.org/10.1016/j.jclepro.2015.04.098
40. IMF. (2011, July 19). Beyond GDP - Measuring Progress in a Changing World [Text]. Collaboration in Research and Methodology for Official Statistics (CROS) - European Commission. https://ec.europa.eu/eurostat/cros/content/38-beyond-gdp\_en
41. Ivkovic, A. F. (2016). Limitations of the Gdp as a Measure of Progress and Well-Being. Ekonomski Vjesnik, 29(1), 257–272.
42. Iwata, H., & Okada, K. (2014). Greenhouse gas emissions and the role of the Kyoto Protocol. Environmental Economics and Policy Studies, 16(4), 325–342. https://doi.org/10.1007/s10018-012-0047-1
43. Iwuoha, S. (2018). Carbon Policies and Potential Leakage: A Bridge-to-Cross in Canada’s Journey to a Lower Carbon Economy. Geopolitics of Energy, 40(1), 9–16.
44. Iwuoha, S., & Onochie, J. I. (2022). Time Series Characteristics of Canada’s Beyond GDP Indicators. Advances in Management and Applied Economics, 79–94. https://doi.org/10.47260/amae/1256
45. Jayanthakumaran, K., & Liu, Y. (2012). Openness and the Environmental Kuznets Curve: Evidence from China. Economic Modelling, 29(3), 566–576. https://doi.org/10.1016/j.econmod.2011.12.011
46. Jordaan, S. M., Romo-Rabago, E., McLeary, R., Reidy, L., Nazari, J., & Herremans, I. M. (2017). The role of energy technology innovation in reducing greenhouse gas emissions: A case study of Canada. Renewable and Sustainable Energy Reviews, 78, 1397–1409. https://doi.org/10.1016/j.rser.2017.05.162
47. Kimmerer, R. W. (2020). Centering First Nations Concepts of Wellbeing: Toward a GDP-Alternative Index in British Columbia (p. 72). British Columbia Assembly of First Nations. https://www.bcafn.ca/sites/default/files/docs/reports-presentations/BC%20AFN%20FINAL%20PRINT%202020-11-23.pdf
48. Kneese, A. V., Ayres, R. U., & d’Arge, R. C. (2015). Economics and the Environment: A Materials Balance Approach. Routledge.
49. Lee, S. (2020). Location and scale-based CUSUM test with application to autoregressive models. Journal of Statistical Computation and Simulation, 90(13), 2309–2328. https://doi.org/10.1080/00949655.2020.1775833
50. Maaloul, A. (2018). The effect of greenhouse gas emissions on cost of debt: Evidence from Canadian firms. Corporate Social Responsibility and Environmental Management, 25(6), 1407–1415. https://doi.org/10.1002/csr.1662
51. Maamoun, N. (2019). The Kyoto protocol: Empirical evidence of a hidden success. Journal of Environmental Economics and Management, 95, 227–256. https://doi.org/10.1016/j.jeem.2019.04.001
52. MacKinnon, J. G. (2013). Thirty Years of Heteroskedasticity-Robust Inference. In X. Chen & N. R. Swanson (Eds.), Recent Advances and Future Directions in Causality, Prediction, and Specification Analysis: Essays in Honor of Halbert L. White Jr (pp. 437–461). Springer. https://doi.org/10.1007/978-1-4614-1653-1\_17
53. Masnadi, M. S., El-Houjeiri, H. M., Schunack, D., Li, Y., Englander, J. G., Badahdah, A., Monfort, J.-C., Anderson, J. E., Wallington, T. J., Bergerson, J. A., Gordon, D., Koomey, J., Przesmitzki, S., Azevedo, I. L., Bi, X. T., Duffy, J. E., Heath, G. A., Keoleian, G. A., McGlade, C., … Brandt, A. R. (2018). Global carbon intensity of crude oil production. Science, 361(6405), 851–853. https://doi.org/10.1126/science.aar6859
54. McGregor, S. L. T. (2003). Economic Indicators and Alternatives to the GDP. McGregor Consulting. http://www.consultmcgregor.com/documents/resources/GDP\_and\_GPI.pdf
55. Millington, D., Hossain, N. A. K. M., Vypovska, A., Goddard, K., & Sanin, M. (2020). The Economic Effectiveness of Different Carbon Pricing Options to Reduce Carbon Dioxide Emissions (No. 189). Canadian Energy Research Institute. https://ceri.ca/assets/files/Study\_189\_Full\_Report.pdf
56. Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive Statistics and Normality Tests for Statistical Data. Annals of Cardiac Anaesthesia, 22(1), 67–72. https://doi.org/10.4103/aca.ACA\_157\_18
57. Nchor, D., & Adamec, V. (2016). Investigating the Stability of Money Demand in Ghana. Procedia - Social and Behavioral Sciences, 220, 288–293. https://doi.org/10.1016/j.sbspro.2016.05.501
58. Nkoro, E., & Uko, A. K. (2013). A Generalized Autoregressive Conditional Heteroskedasticity Model of the Impact of Macroeconomic Factors on Stock Returns: Empirical Evidence from the Nigerian Stock Market. International Journal of Financial Research, 4(4), 38–51.
59. Obergassel, W., Mersmann, F., Ott, H. E., & Wang-Helmreich, H. (2015). Phoenix from the ashes: An analysis of the Paris Agreement to the United Nations Framework Convention on Climate Change – Part I. Environmental Law, 27, 243–262.
60. Okumuş, İ., & Bozkurt, C. (2020). The Effects of Economic Growth on Environment for Different Income Group Countries. Gaziantep University Journal of Social Sciences, 19, 238–255. https://doi.org/10.21547/jss.593962
61. Rani, N., & Mandal, A. (2020, August 6). All Inclusive Economic Development: The GDP alternative offers a better measure of progress | Policy Circle [Article]. Policy Circle. https://www.policycircle.org/economy/all-inclusive-economic-development-why-this-gdp-alternative-is-a-better-measure-of-progress/
62. Ritchie, H., & Roser, M. (2017). CO₂ and Greenhouse Gas Emissions: Canada. Our World in Data. https://ourworldindata.org/co2/country/canada
63. Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M., & Owen, A. (2016). Decoupling global environmental pressure and economic growth: Scenarios for energy use, materials use and carbon emissions. Journal of Cleaner Production, 132, 45–56. https://doi.org/10.1016/j.jclepro.2015.06.100
64. Seto, K. C., Davis, S. J., Mitchell, R. B., Stokes, E. C., Unruh, G., & Ürge-Vorsatz, D. (2016). Carbon Lock-In: Types, Causes, and Policy Implications. Annual Review of Environment and Resources, 41(1), 425–452. https://doi.org/10.1146/annurev-environ-110615-085934
65. Shahbaz, M., Solarin, S. A., Mahmood, H., & Arouri, M. (2013). Does financial development reduce CO2 emissions in Malaysian economy? A time series analysis. Economic Modelling, 35, 145–152. https://doi.org/10.1016/j.econmod.2013.06.037
66. Singhania, M., & Saini, N. (2021). Demystifying pollution haven hypothesis: Role of FDI. Journal of Business Research, 123, 516–528. https://doi.org/10.1016/j.jbusres.2020.10.007
67. Sun, Y. (2013). A heteroskedasticity and autocorrelation robust F test using an orthonormal series variance estimator. The Econometrics Journal, 16(1), 1–26. https://doi.org/10.1111/j.1368-423X.2012.00390.x
68. Talaş, E., Kaplan, F., & Çelik, A. K. (2013). Model Stability Test of Money Demand by Monthly Time Series Using CUSUM and MOSUM Tests: Evidence from Turkey. Research in World Economy, 4(2). https://doi.org/10.5430/rwe.v4n2p36
69. Tan, S., Yang, J., Yan, J., Lee, C., Hashim, H., & Chen, B. (2017). A holistic low carbon city indicator framework for sustainable development. Applied Energy, 185, 1919–1930. https://doi.org/10.1016/j.apenergy.2016.03.041
70. Umeozor, E., Iwuoha, S., & Vypovska, A. (2019). Supply Costs and Emission Profiles of Petrochemical Products in Selected Hubs (No. 181). https://ceri.ca/assets/files/Study\_181\_Full\_Report.pdf
71. Urbain, J.-P. (2012). Exogeneity in Error Correction Models. Springer Science & Business Media.
72. US EPA. (2016, January 12). Global Greenhouse Gas Emissions Data [Overviews and Factsheets]. United States Environmental Protection Agency. https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data
73. Victor, D. G. (2011). The Collapse of the Kyoto Protocol and the Struggle to Slow Global Warming. Princeton University Press.
74. Victor, P. A. (2017). Pollution: Economy and Environment (Vol. 18). Routledge, Taylor Francis Group.
75. Victor, P. A., & Dolter, B. (2017). Handbook on Growth and Sustainability. Edward Elgar Publishing.
76. Volkova, V. M., & Plankina, V. L. (2013). The Research of Distribution of the Ramsey RESET-Test Statistic. Proceedings of the International Workshop. Applied Methods of Statistical Analysis. Applications in Survival Analysis, Reliability and Quality Control., Novosibirsk. https://amsa.conf.nstu.ru/amsa2013/AMSA2013\_proceedings.pdf#page=265
77. Whitby, A. (WFC), Seaford, C., & Berry, C. (2014). BRAINPOol Project: Beyond GDP - From Measurement to Politics and Policy Deliverable (Project Report D5.2; p. 68). European Union. https://neweconomics.org/uploads/images/2018/01/BRAINPOoL-Project-Final-Report.pdf
78. Whittenberg, L. (2021). Methane: The other important greenhouse gas. Environmental Defense Fund. https://www.edf.org/climate/methane-other-important-greenhouse-gas
79. Yang, Y., Brammer, J. G., Wright, D. G., Scott, J. A., Serrano, C., & Bridgwater, A. V. (2017). Combined heat and power from the intermediate pyrolysis of biomass materials: Performance, economics and environmental impact. Applied Energy, 191, 639–652. https://doi.org/10.1016/j.apenergy.2017.02.004

1. International School of Management, Paris, France. e-mail: iwuohasochi@yahoo.com [↑](#footnote-ref-1)
2. Zicklin School of Business, Baruch College, City University of New York, United States. e-mail: joseph.onochie@baruch.cuny.edu [↑](#footnote-ref-2)