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

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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.

Keywords: Greenhouse gas, Stationarity, Cointegration, Error correction, GDP-alternatives.

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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 (CO_2) 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 CO_2 (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.

1.1 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.

2. 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, CO_2 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 CO_2 emissions constitute the largest proportion of GHG emissions (Figures 1 and 2), emissions time series data, however, show that the trends in CO_2 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 (CH_4) 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 CH_4 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).

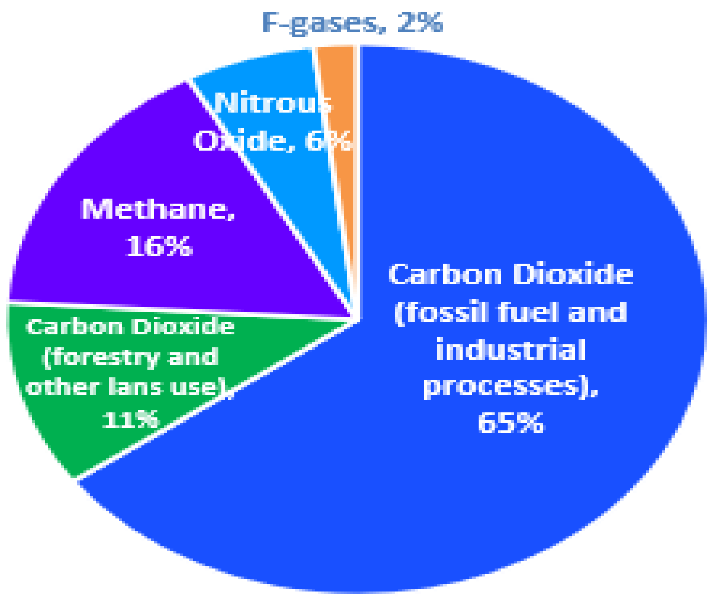

Figure 1: 2015 Global GHG emissions share by gas

Source: US EPA (2016).

Note: Total (or aggregate) GHG emissions is comprised of CO_2, CH_4, Nitrous oxide (N_2O), and Fluorinated gases or F-gases (nitrogen trifluoride, hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride.

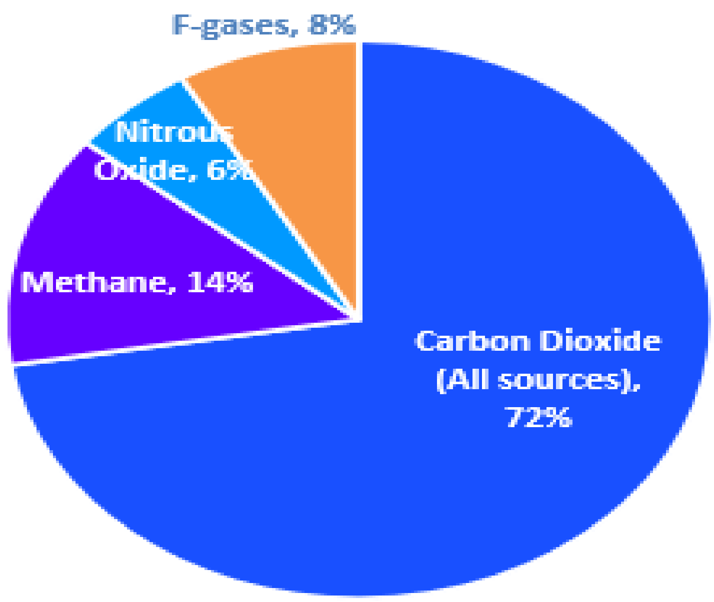

Figure 2: Canada's 2016 GHG emissions share by gas

Data Source: Ritchie & Roser, 2017.

Note: Canada's Aggregate GHG emission was ~779 megatonnes (Mt) CO_2 equivalent (CO_2e) (Ritchie & Roser, 2017).

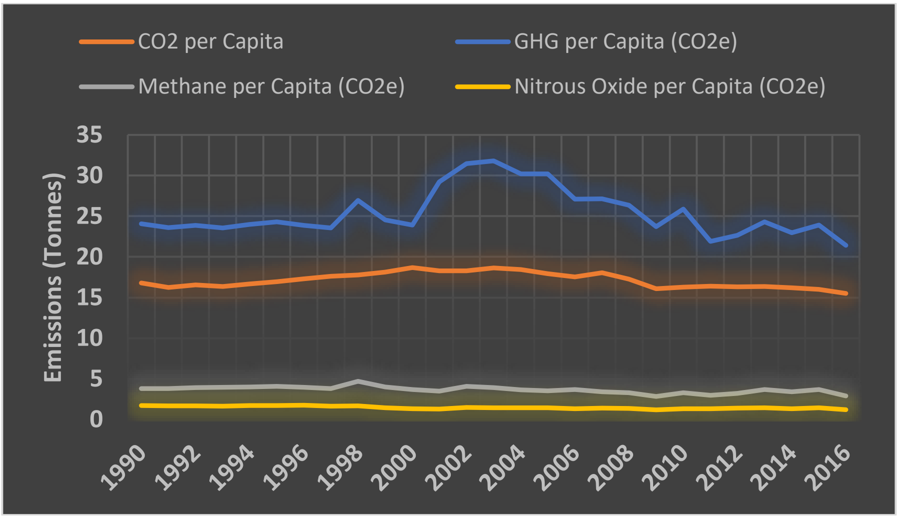

Figure 3: Canada's per capita GHG emissions by gas from 1990 to 2016

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

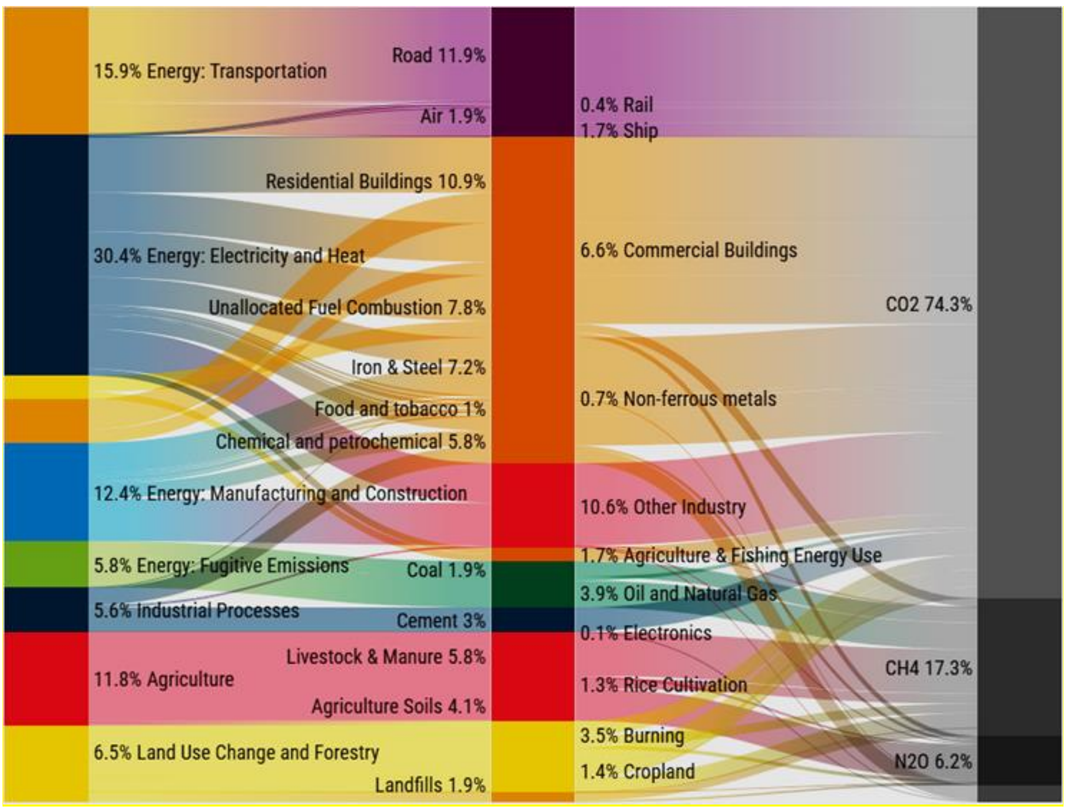

Figure 4: 2016 Global GHG emissions by sector, end-use, and gas (Ge & Friedrich, 2020).

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 (CO_2, CH_4, nitrous oxide - N_2O, 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.

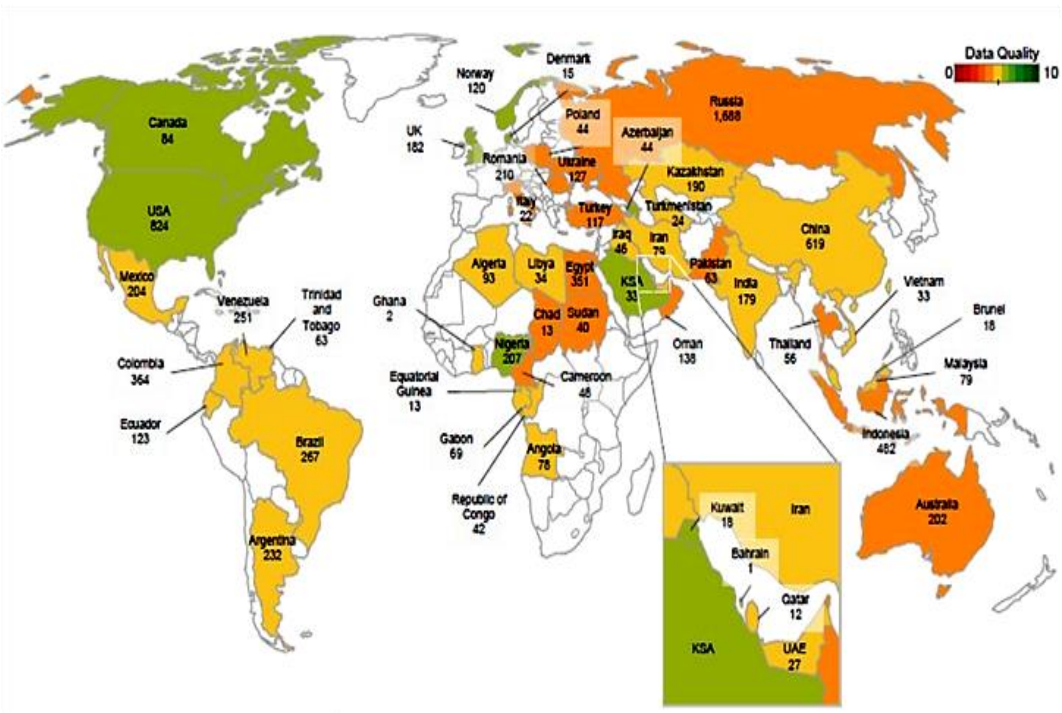

Figure 5: Data quality scores of volume-weighted-average crude oil production GHG intensity estimates

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 CO_2 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).

3. 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):

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 \Delta X_t + \beta_1 X_{t-1} + \mathcal{E}_t \quad (1)$$

where ΔY_t is the change in the dependent variable, α_0 is a constant (or the intercept), α_1 is the error correction rate, Y_{t-1} is the dependent variable lagged by one period, β_0 is the coefficient of the change in the explanatory variable, ΔX_t is the change in the explanatory (or independent) variable, β_1 is the coefficient of the lagged value of the explanatory variable, X_{t-1} is the explanatory variable lagged by one period, and $\mathcal{E}_t$ 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.

4. 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.

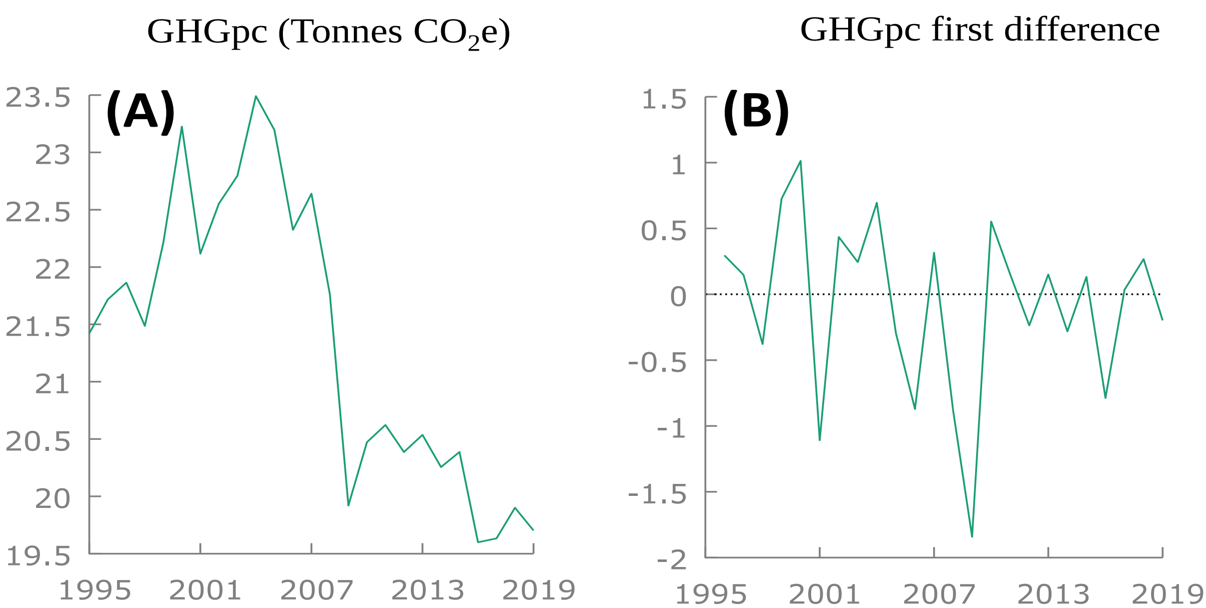

Figure 6: GHGpc time series plots by level and first difference (growth level)

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).

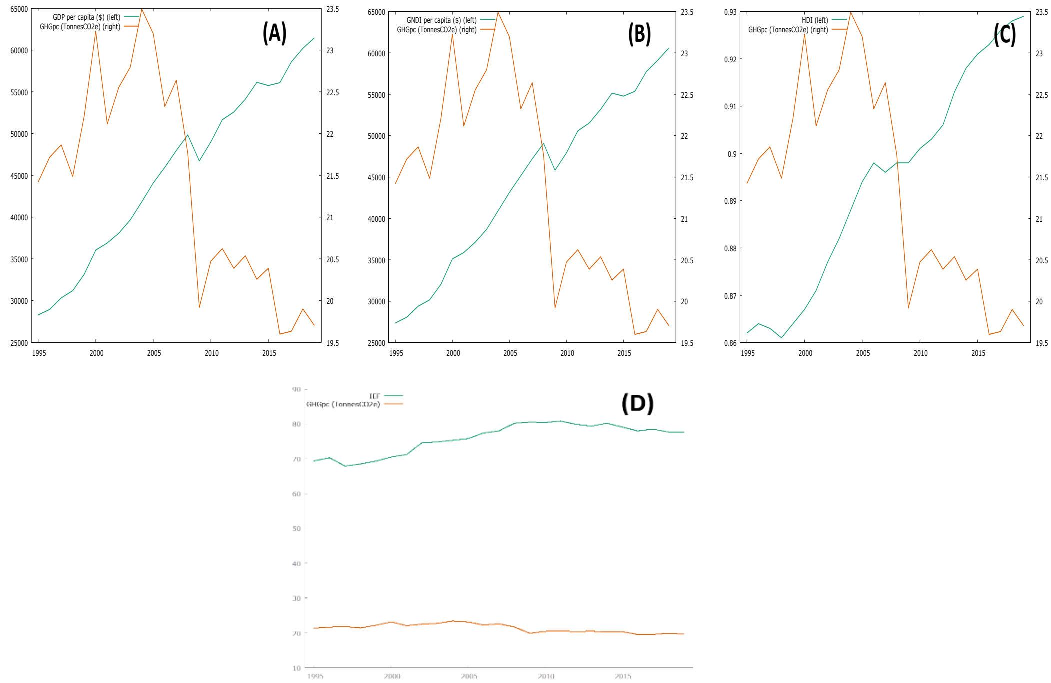

Figure 7: Paired time-series plots (by level) of GHGpc and GDP-Alternative measures

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	Autocorre lation	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 & Demirel (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).

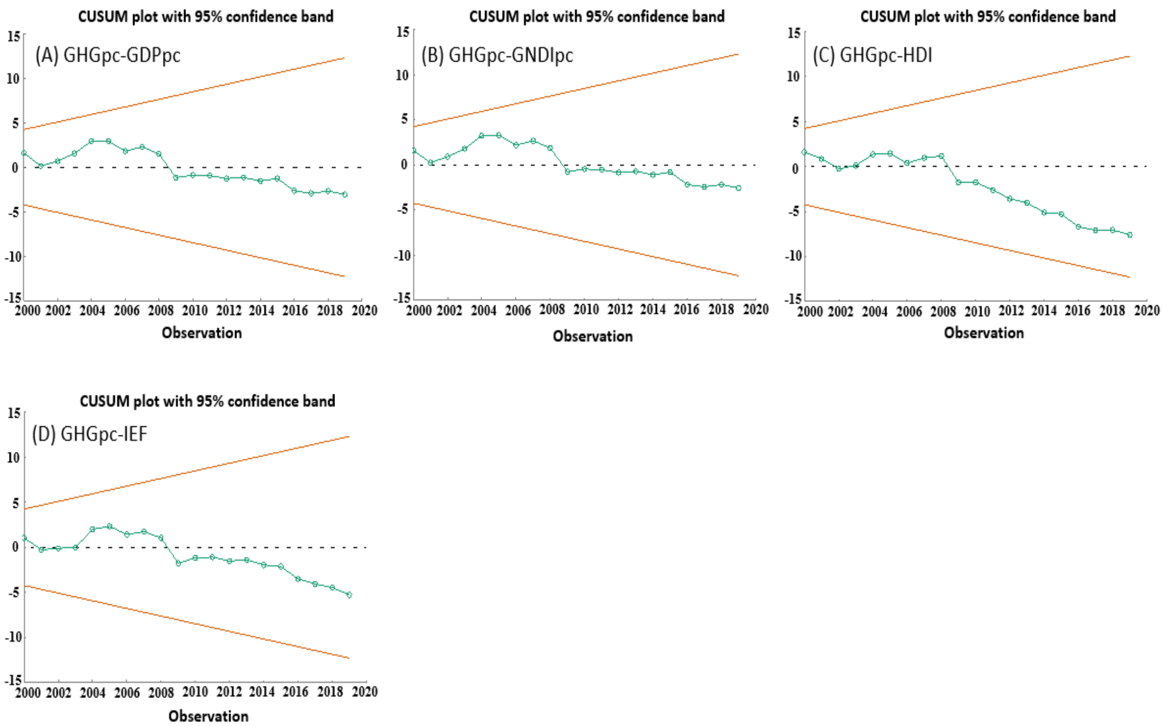

Figure 8: CUSUM test for ECM parameter stability - Results for GHGpc versus the growth measures

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

4.1 Time Series Plots

Over the 1995 - 2019 time series period, the GHGpc level shows multiple peaks, with the maximum GHGpc of 23.5 tonnes CO_2e (tCO_2e) 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.

4.2 Descriptive Statistics

Canada's per capita mean and median GHG emissions were similar between 1995 and 2019, being 21.4 tCO_2e and 21.5 tCO_2e respectively (Figure 6A and Table 1). The GHGpc time series is positive, fairly symmetrical, and platykurtic.

4.3 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.

4.4 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 $p\text{-value} < 0.05$, 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.

4.5 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):

a) The ECM specification is adequate.
b) Heteroskedasticity and ARCH are not present.
c) The ECM error is normally distributed
d) There is no autocorrelation, and
e) 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.

5. 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.

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