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Perspective

Inequality is driving the climate crisis: A longitudinal analysis of province-level carbon emissions in Canada, 1997–2020

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ABSTRACT

The authors conduct a comprehensive analysis of the relationship between carbon emissions and income inequality for the Canadian provinces for the 1997 to 2020 period. The results indicate that the short-run and long-run effects of the income share of the top 10 % and the top 5 % on province-level emissions are positive, robust to various model specifications, net of multiple demographic and economic factors, not sensitive to exogenous shocks or outlier cases, symmetrical, statistically equivalent for emissions from different sectors, and their short-term effects do not vary in magnitude through time. The findings also consistently show that the estimated effect of the Gini coefficient on province-level emissions is not statistically significant. Overall, the results underscore the importance in modeling the effects of income inequality measures that quantify different characteristics of income distributions, and they are very consistent with analytical approaches regarding power concentration, overconsumption, and status competition that suggest that a higher concentration of income leads to growth in anthropogenic carbon emissions.

1. Introduction

Income inequality is a topic of substantial and growing interest within scientific research on the anthropogenic drivers of climate change [1–5]. Many studies focus on how carbon dioxide (CO_2) emissions is associated with income inequality in global, national, and subnational contexts [6–22]. The inclusion of and engagement with this research in synthesis and policy documents, such as the IPCC assessment reports and national climate assessments, has also grown in recent years [23,24]. This inclusion and engagement is perhaps not surprising, given that income inequality is found in many studies to be associated with anthropogenic emissions, which highlights the necessity for equity considerations when addressing both the societal causes and consequences of the climate crisis [10,25–31].

We add to this important area of climate change research by focusing on the relationship between CO_2 emissions and income inequality in Canada, which is one of the world's largest emitters, ranking tenth in the year 2020 for territorial CO_2 emissions [32] and eleventh for consumption-based (i.e., adjusted for trade) CO_2 emissions [33]. Using a range of statistical modeling techniques, we conduct an analysis of the effects of inequality on emissions for the Canadian provinces for the 1997 to 2020 period. While other recent research investigates the relationship between carbon emissions and income inequality for Canada as a whole [34], to our knowledge, the present study is the first to analyze this relationship in a longitudinal, Canadian cross-province context. Without question, Canada's economy is energy-intensive and the nation is among the world's greatest carbon polluters. We suggest a focus on province-level emissions is critical, given the power provinces have in regulating emissions and implementing measures that could reduce inequality. We consider multiple measures of income inequality, including the income share of the top 10 %, income share of the top 5 %, and the Gini coefficient. The inclusion of the three inequality measures is important on both measurement and substantive grounds: they capture different characteristics of income distributions and are therefore well suited to empirically evaluate the arguments of different analytical approaches.

One analytical approach suggests that a higher concentration of income is likely to be associated with higher levels and growth in

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anthropogenic CO_2 emissions and other forms of pollution. Those in the top of the income distribution are more likely to be owners of carbon-polluting firms, be major investors in carbon-intensive sectors, serve on the boards of firms and corporations, consume more goods and services with substantial environmental impacts, live in larger spaces and own multiple homes, and participate much more frequently in expensive carbon-intensive activities, such as air travel [14,17,35]. They are also likely to utilize their economic resources to gain disproportionate influence in climate, energy, and other areas of environmental policy, as they benefit financially from carbon-polluting economic activities [36–42]. A second approach argues that a higher concentration of income causes enhanced status competition, leading to increased CO_2 emissions. Middle- and low-income households increase their spending to emulate the highly visible and culturally desirable carbon-intensive lifestyles of high-income individuals and households [43]. This is referred to as both the "Veblen effect" [44,45] and the "influencer effect" [17], and is amplified when there is a greater concentration of income and wealth [46,47]. Many researchers consider concentration measures, such as the income share of the top 10 % and the top 5 %, to be ideal for empirically evaluating the propositions of these two approaches, with multiple studies finding empirical support for them [1,13,16,34,47].

A third analytical approach suggests that CO_2 emissions are negatively associated with income inequality since the marginal propensity to emit decreases as household income increases [48–50]. Each additional dollar of household income will lead to a larger marginal increase in emissions in low-income households compared to middle-income households, and in middle-income households compared to high-income households. A fourth approach, influenced by Keynesian thinking, argues that the marginal propensity to consume declines with increases in household income, and therefore, a top-to-bottom redistribution of income, which reduces income inequality, could increase

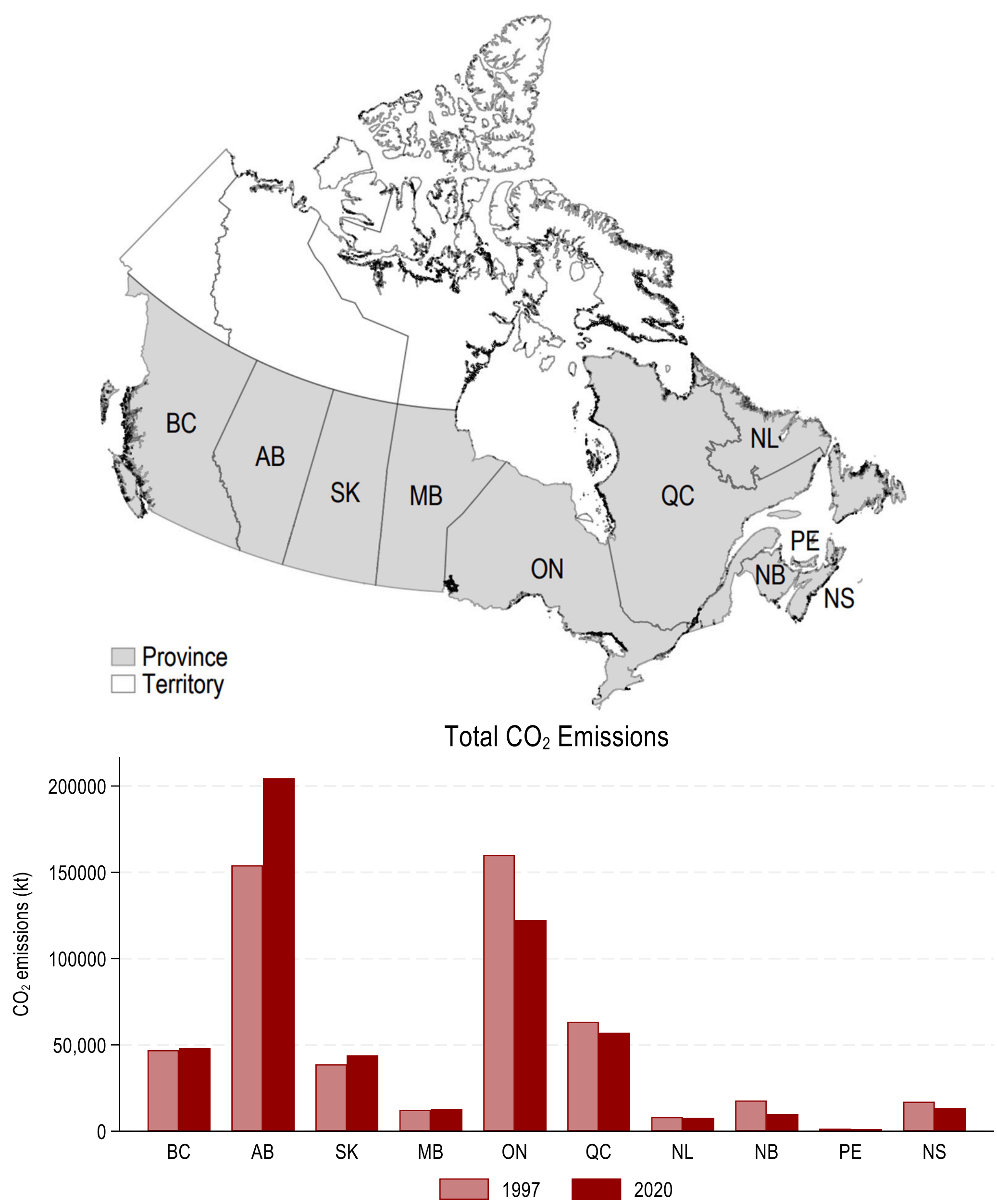

Fig. 1. Canadian Provinces and Their Total CO_2 Emissions (kt) in 1997 and 2020. Notes: Abbreviations are used for provinces: BC = British Columbia, AB = Alberta, SK = Saskatchewan, MB = Manitoba, ON = Ontario, QC = Quebec, NL = Newfoundland and Labrador, NB = New Brunswick, PE = Prince Edward Island, and NS = Nova Scotia; for emissions, provinces are listed in order from west to east based on their geographical locations.

overall consumption and CO_2 emissions [16]. Given how it measures inequality within distributions, the Gini coefficient is often considered the more appropriate income inequality measure for testing the arguments of these two approaches, with prior research yielding inconsistent findings [20,51–54].

Fig. 1 provides a map of the ten Canadian provinces and bar charts for their total CO_2 emissions (i.e., territorial emissions, also known as production-based emissions, for all sectors combined) in 1997 and 2000, and Fig. 2 includes bar charts for the three income inequality measures: income share of the top 10 %, income share of the top 5 %, and the Gini coefficient (see Methods section for descriptions of these data). Levels and changes in emissions differ greatly, with Alberta having the largest emissions in 2020 (204,324.30 kt), followed by Ontario (122,299.28 kt) and Quebec (57,113.66 kt), with Prince Edward Island having the smallest total emissions in 2020 (1124.89 kt), followed by Newfoundland and Labrador (7766.87 kt) and New Brunswick (9909.85 kt). Four provinces increased their emissions from 1997 to 2020 (Alberta, British Columbia, Manitoba, Saskatchewan), while six decreased their emissions to some extent (New Brunswick, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec).

For the inequality measures in Fig. 2, income share of the top 10 % for the year 2020 was greatest in Alberta (36.80 %), followed by Ontario (32.00 %) and British Columbia (31.00 %), with Prince Edward Island having the lowest (14.60 %), followed by New Brunswick (16.10 %), and Nova Scotia (17.90 %). Four provinces experienced an increase from 1997 to 2020 (Alberta, Newfoundland and Labrador, Quebec, Saskatchewan), while six experienced a decrease (British Columbia, Manitoba, New Brunswick, Nova Scotia, Ontario, Prince Edward Island). Similar but not identical patterns occur for income share of the top 5 %: Alberta had the highest level in 2020 (25.10 %), followed by Ontario (20.80 %) and British Columbia (20.30 %), with Prince Edward Island having the lowest (9.00 %), followed by New Brunswick (9.60 %), and Nova Scotia (10.80 %). Alberta, British Columbia, Newfoundland and Labrador, Quebec, and Saskatchewan experienced increases from 1997 to 2020, while the other five provinces experienced decreases in income share of the top 5 %. Ontario had the largest Gini coefficient in 2020 (0.29), followed by British Columbia (0.28) and five provinces with coefficients of 0.27. Nova Scotia, Prince Edward Island, and Quebec had the lowest in 2020, each with a value of 0.26. All provinces except Newfoundland and Labrador and Prince Edward Island experienced decreases in their Gini coefficient from 1997 to 2020.

Informed by prior research and the various analytical approaches to the relationship between emissions and income inequality, our analysis focuses on both the short-run and long-run effects of income inequality on province-level CO_2 emissions. We also assess if the effects of inequality are robust to various model specifications, net of multiple economic and demographic factors, symmetrical, sensitive to exogenous shocks, statistically equivalent for emissions from different sectors, and if the short-term effects of inequality on emissions vary in magnitude through time. We turn now to the Methods section, where we describe the analyzed sample and data, as well as the various statistical modeling techniques that we use to conduct the analysis.

2. Data and methods

2.1. Data

The analyzed dataset consists of yearly observations from 1997 to 2020 for the ten provinces in Canada (Alberta, British Columbia, Manitoba, New Brunswick, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec, Saskatchewan). These are the years in which data are currently available for both the dependent variable and the key independent variables. Consistent with prior research on anthropogenic drivers of emissions, the Canadian Territory jurisdictions are excluded from this study because their political structures differ from that of the provinces [55], and there is less data available on the primary independent variables for the territories than for the provinces.

The dependent variable is anthropogenic Total Carbon Dioxide (CO_2) Emissions (i.e., territorial), measured in kilotons (kt). These data are publicly available from Canada's Official Greenhouse Gas Inventory (https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/inventory.html). The independent variables of interest are Income Share of the Top 10 %, Income Share of the Top 5 %, and the Gini Coefficient. These data, which are based upon after tax income for all tax filers, are publicly available from Statistics Canada (https://www.statcan.gc.ca/en/start).

Additional independent variables, which are also obtained from Statistics Canada, include Total Population, GDP Per Capita (chained 2012 dollars), Non-Dependent Population (percent of population aged 15 to 64), Manufacturing as % GDP, Agriculture as % GDP, Services as % GDP, Energy as % GDP, and Fossil Fuels as % GDP. These economic and demographic measures, which capture a range of the characteristics of the provinces, are among the most common controls in the anthropogenic drivers research [2,3,5]. Univariate descriptive statistics for all variables included in the analysis are provided in the table in Appendix 1. The full dataset is available from the lead author upon request, and will also be posted on the lead author's lab website.

2.2. General modeling approach

All models are estimated using Stata (version 18), and all Stata code used for the reported analysis are available from the lead author upon request, and will also be posted on the lead author's lab website. Consistent with much other research on the anthropogenic drivers of CO_2 emissions, all nonbinary variables are transformed into logarithmic form. This means the models estimate elasticity coefficients where the coefficient for the independent variable is the estimated net percentage change in the dependent variable associated with a 1 % increase in the independent variable [56].

With the exception of Table 5, Table 6, and Appendix 2, all reported models are estimated with the xtreg, fe command. Given the relatively small number of cases (10 provinces) and moderate size of T (24 yearly observations per province), hc2 clustered robust standard errors are estimated with all xtreg models, with the *p*-values computed using adjusted degrees of freedom [57,58]. The hc2 standard errors tend to produce slightly more conservative confidence intervals than other standard error approaches, leading to more conservative hypothesis testing [58]. The xtreg, fe command uses the within estimator to account for province-level fixed effects, and temporal fixed effects are derived from the inclusion of year-specific dummy variables [59].

All estimated models are dynamic, meaning they include the lagged dependent variable as a control. Panel data are often autoregressive, meaning the data tend to be correlated over time, and excluding the lag of the dependent variable from the model will result in omitted variable bias if the outcome variable is truly a function of their past value [60]. Including the lagged dependent variable also allows for the estimation of both short-run and long-run effects of independent variables. The general equation for Model 3 in Table 1 and Table 2 (the first model in each of the two tables to include both relevant inequality variables) is as follows:

$$
\begin{aligned}
\mathrm{CO_2Emissions_{i,t}} = {} & \lambda_1 \mathrm{CO_2Emissions_{i,t-1}} \\
& + \beta_1 \text{Income Share of Top 10\% or Top 5\%}_{\mathrm{i,t}} \\
& + \beta_2 \text{Gini Coefficient}_{\mathrm{i,t}} + \beta_3 \text{Total Population}_{\mathrm{i,t}} \\
& + \beta_4 \text{GDP per capita}_{\mathrm{i,t}} \\
& + \beta_5 \text{NonDependent Population}_{\mathrm{i,t}} + \alpha_{\mathrm{i}} + u_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}}.
\end{aligned}
$$

The short-run estimated effects are β_1 to β_5, and the long-run effects are estimated by dividing each short-run estimate by 1-λ_1. The long-run effects are calculated using the community-contributed lreff command

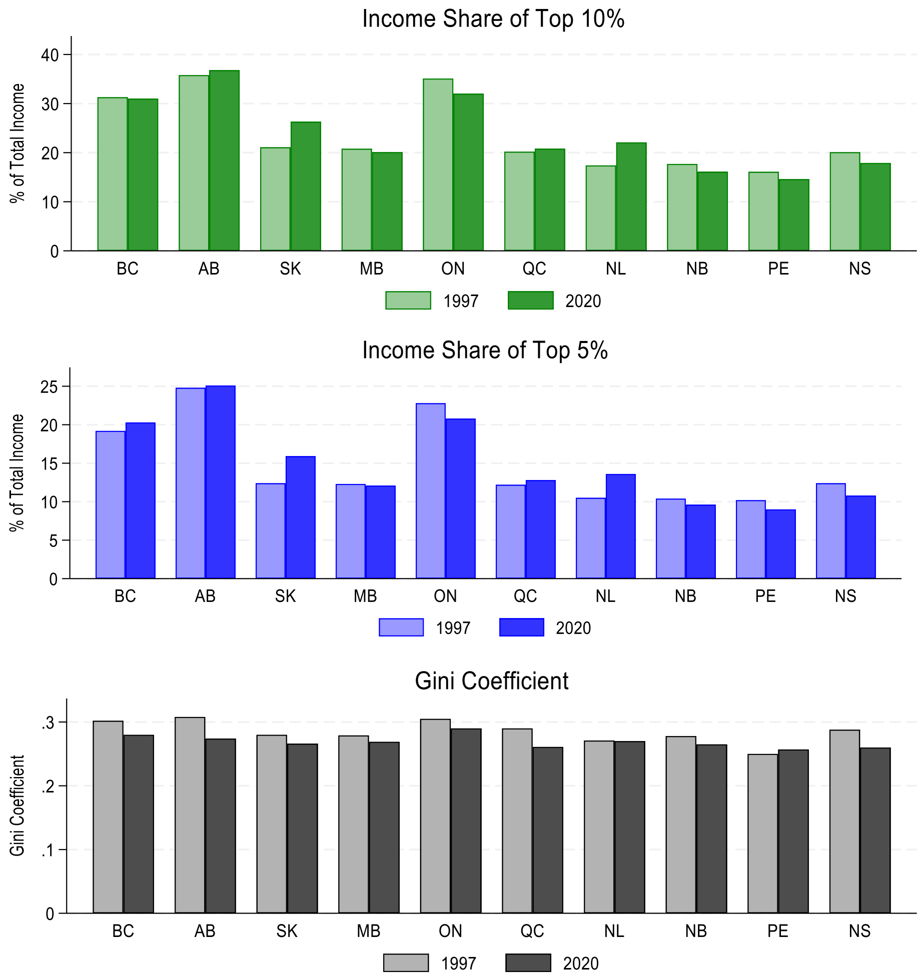

Fig. 2. Income Share of Top 10 %, Income Share of Top 5 %, and Gini Coefficient for Canadian Provinces in 1997 and 2020. Notes: Abbreviations are used for provinces: BC = British Columbia, AB = Alberta, SK = Saskatchewan, MB = Manitoba, ON = Ontario, QC = Quebec, NL = Newfoundland and Labrador, NB = New Brunswick, PE = Prince Edward Island, and NS = Nova Scotia; provinces are listed in order from west to east based on their geographical locations.

in Stata [61], which serves as a wrapper for the nlcom command that computes standard errors using the delta method. The short-run estimates correspond to the immediate change in emissions, while the long-run effects estimate the total change in emissions over time.

2.3. Asymmetrical analysis

For the asymmetrical analysis reported in Table 3 and Table 4, we follow the standard approach to modeling asymmetry by including the positive and negative partial sums of each income inequality measure in the models [62–65]. $x_{i,t}$ is decomposed as $x_{i,t} = x_{i,0} + x^{+}_{i,t} + x^{-}_{i,t}$, where $x^{+}_{i,t}$ and $x^{-}_{i,t}$ are partial sums around a threshold of zero:

$$x^{+}_{i,t} = \sum_{j=1}^{t} \Delta x^{+}_{i,t} = \sum_{j=1}^{t} max\left(\Delta x^{+}_{i,t}, 0\right)$$

$$x^{-}_{i,t} = \sum_{j=1}^{t} \Delta x^{-}_{i,t} = \sum_{j=1}^{t} min\left(\Delta x^{-}_{i,t}, 0\right)$$

In other words, two series are generated that estimate the running totals of the positive ($x^{+}_{i,t}$) and negative ($x^{-}_{i,t}$) changes in $x_{i,t}$. A Wald test is then used to test whether the coefficients of the two sums are equal. If they are statistically different then there is evidence of asymmetry. The partial sums are generated in Stata 18 using the community contributed xtasysum command [66].

2.4. Testing the simultaneous effects of income inequality on energy and non-energy emissions

We use a stacked regression analysis, reported in Table 5 and Table 6, to test whether the effects of income inequality are different on energy and non-energy CO_2 emissions. "Stacking" is a procedure that appends the two samples of data together, which doubles the number observations used in the analysis [67]. A new dependent variable is generated that equals the value of energy emissions in the first half of the data and equals the value of non-energy emissions in the second half. Independent variables, unit-specific intercepts, and time-specific intercepts are generated for each sample too. A useful property of this approach is that the coefficients and standard errors are equal to the non-stacked estimates, and a simple Wald test can be performed to test whether the effects are equivalent.

2.5. Interactions between income inequality and time

The models reported in Table 7 include interactions between income share of the top 10 % and the top 5 % and the dummy variables for year. The reference year is 1997, and the coefficient for the main effect of each inequality measure is it's estimated short-term effect on CO_2 emissions in 1997. The short-term effect of the inequality measures for the other time points equals the sum of the coefficient for their main effect (i.e., their effect in 1997) and the appropriate interaction term if the latter is statistically significant [59].

Table 1
Coefficients for the regression of total CO_2 emissions for Canada Provinces, 1997 to 2020.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Income Share of Top 10 %	0.150^		0.170*	0.172^	0.161*	0.182*	0.163*	0.172*
	(0.056)		(0.056)	(0.068)	(0.054)	(0.051)	(0.059)	(0.056)
Gini Coefficient		−0.054	−0.177	−0.173	−0.191	−0.194	−0.183	−0.181
		(0.139)	(0.145)	(0.164)	(0.157)	(0.151)	(0.161)	(0.146)
Total Population	0.396**	0.308	0.387**	0.383**	0.405**	0.379**	0.429**	0.387**
	(0.090)	(0.173)	(0.088)	(0.075)	(0.093)	(0.092)	(0.092)	(0.089)
GDP Per Capita	0.175	0.217^	0.179	0.176	0.144	0.067	0.218^	0.169
	(0.079)	(0.091)	(0.084)	(0.094)	(0.077)	(0.195)	(0.084)	(0.100)
Non-Dependent Population	0.797	0.734	0.834	0.856	1.105^	0.792	0.825	0.834
	(0.475)	(0.648)	(0.463)	(0.608)	(0.465)	(0.467)	(0.429)	(0.466)
Manufacturing as % GDP				−0.006				
				(0.078)				
Agriculture as % GDP					−0.052			
					(0.031)			
Services as % GDP						−0.140		
						(0.290)		
Energy as % GDP							0.043	
							(0.028)	
Fossil Fuels as % GDP								0.002
								(0.006)
Lagged Carbon Emissions	0.756***	0.825***	0.748***	0.748***	0.729***	0.750***	0.743***	0.746***
	(0.037)	(0.042)	(0.036)	(0.043)	(0.043)	(0.037)	(0.035)	(0.040)
Long-Run Effects for	0.616***		0.673***	0.680***	0.595***	0.727***	0.634***	0.677***
Income Share of Top 10 %	(0.188)		(0.181)	(0.208)	(0.137)	(0.189)	(0.177)	(0.175)
R-squared within	0.874	0.875	0.876	0.876	0.878	0.876	0.877	0.876

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, p-values computed using adjusted degress of freedom); $N = 240$, with 24 observations per province; non-binary variables are in logarithmic form; $^{***}p < .001$ $^{**}p < .01$ $^{*}p < .05$ $^{\hat{}}p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts; p-value for income share of top 10 % is 0.053 in Model 1 and 0.062 in Model 4; long-run effects estimated with Thombs' user-generated lreff command in Stata.

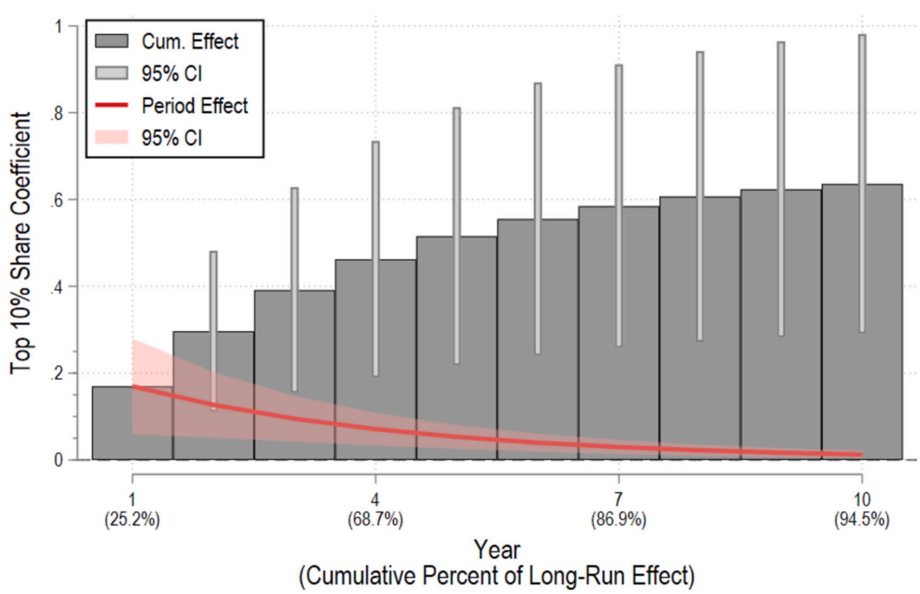

Fig. 3. The long-run effect of the income share of the top 10 % on total CO_2 emissions. Notes: Based on Model 3 in Table 1; Cum. Effect = Cumulative effect; 95 % CI = 95 % confidence intervals.

3. Results

Table 1 reports eight dynamic models of province-level CO_2 emissions for the 1997 to 2020 period, which focus on the short-run and long-run effects of the income share of the top 10 % and the Gini coefficient. All models control for population size, GDP per capita, the relative size of the non-dependent population, lagged CO_2 emissions, and include both case-specific and year-specific fixed effects. Models 4 through 8 include a different economic sector measure as an additional control: manufacturing as % GDP, agriculture as % GDP, services as % GDP, energy as % GDP, or fossil fuels as % GDP. Since the overall sample size is relatively small, we do not estimate fully saturated models that include all the control variables. Models 1 and 2 focus on the income inequality measures separately, while Models 3 through 8 include both. As a reminder, elasticity coefficients are reported, where the coefficient for an independent variable is the estimated net percentage change in the dependent variable associated with a 1 % increase in the

Table 2
Coefficients for the regression of total CO_2 emissions for Canada Provinces, 1997 to 2020.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Income Share of Top 5 %	0.122ˆ		0.136*	0.138ˆ	0.129*	0.148*	0.131*	0.138*
	(0.046)		(0.046)	(0.056)	(0.044)	(0.043)	(0.048)	(0.046)
Gini Coefficient		−0.055	−0.172	−0.167	−0.184	−0.192	−0.178	−0.176
		(0.139)	(0.139)	(0.158)	(0.150)	(0.145)	(0.155)	(0.140)
Total Population	0.364**	0.308	0.351**	0.346**	0.369*	0.339*	0.393**	0.350*
	(0.084)	(0.173)	(0.086)	(0.075)	(0.094)	(0.092)	(0.096)	(0.089)
GDP Per Capita	0.175ˆ	0.217ˆ	0.179	0.175	0.146	0.047	0.217ˆ	0.167
	(0.071)	(0.091)	(0.076)	(0.086)	(0.068)	(0.210)	(0.081)	(0.096)
Non-Dependent Population	0.854	0.734	0.896	0.924	1.148ˆ	0.851	0.884	0.897
	(0.450)	(0.648)	(0.433)	(0.576)	(0.448)	(0.440)	(0.406)	(0.437)
Manufacturing as % GDP				−0.007				
				(0.077)				
Agriculture as % GDP					−0.050			
					(0.030)			
Services as % GDP						−0.165		
						(0.288)		
Energy as % GDP							0.042	
							(0.026)	
Fossil Fuels as % GDP								0.002
								(0.006)
Lagged Carbon Emissions	0.764***	0.825***	0.758***	0.758***	0.740***	0.761***	0.753***	0.756***
	(0.035)	(0.042)	(0.033)	(0.039)	(0.040)	(0.035)	(0.034)	(0.037)
Long-Run Effects for Income Share of Top 5 %	0.518**		0.563***	0.571**	0.494***	0.621***	0.529***	0.567***
	(0.164)		(0.160)	(0.187)	(0.124)	(0.174)	(0.153)	(0.157)
R-squared within	0.874	0.876	0.876	0.876	0.878	0.876	0.877	0.876

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, p-values computed using adjusted degress of freedom); $N = 240$, with 24 observations per province; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts; p-value for income share of top 5 % is 0.052 in Model 1 and 0.065 in Model 4; long-run effects estimated with Thombs' user-generated lreff command in Stata.

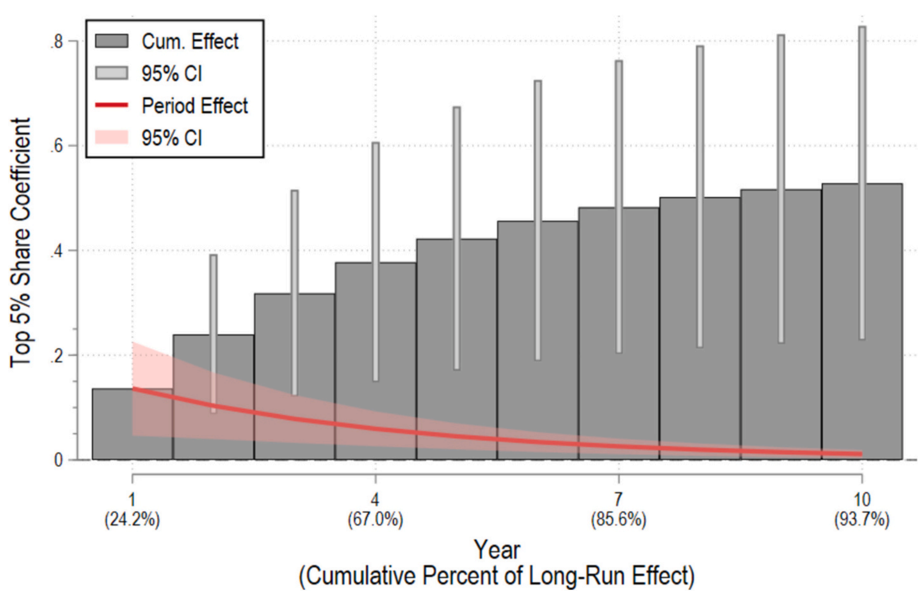

Fig. 4. The long-run effect of the income share of the top 5 % on total CO_2 emissions. Notes: Based on Model 3 in Table 2; Cum. Effect = Cumulative effect; 95 % CI = 95 % confidence intervals.

independent variable.[1]

The findings indicate that the income share of the top 10 % has a positive and statistically significant short-run effect on CO_2 emissions, while the estimated effect of the Gini coefficient is not statistically significant. The point estimate of the elasticity coefficient for income share of the top 10 % is relatively consistent across models, ranging from 0.150 in Model 1 to 0.182 in Model 6. For Model 3, which is the first to include both inequality measures, the point estimate is 0.170, meaning that in the short run, a 1 % increase in the income share of the top 10 % leads to a 0.170 % increase in CO_2 emissions.

The long-run effect of the income share of the top 10 % is provided towards the bottom of the table (the long-run effect of the Gini coefficient is not estimated and reported since the short-run effect is not significantly different than zero). For Model 3 it is 0.673 and statistically significant, meaning that a 1 % increase in the income share of the top 10 % increases CO_2 emissions by 0.673 % over the long run. Fig. 3 illustrates the percentage change in emissions over a 10-year period

[1] The results of tests for serial correlation in the errors, using the community contributed xtserialpm command in Stata [68], are not statistically significant for all models in Table 1 and Table 2.

Table 3
Asymmetric regression of total CO_2 emissions for Canada Provinces (short-run effects), 1997 to 2020.

	Top 10 %	Top 5 %
Income Share of Top 10 % (+)	0.171ˆ (0.075)	
Income Share of Top 10 % (−)	0.166 (0.087)	
Income Share of Top 5 % (+)		0.151ˆ (0.061)
Income Share of Top 5 % (−)		0.108 (0.055)
Short-Run Asymmetry (Wald Test)	0.00	0.29

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, *p*-values computed using adjusted degress of freedom); $N = 240$, with 24 observations per province; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts; models control for Gini Coefficient, Total Population, GDP Per Capita, Non-Dependent Population, and Lagged Carbon Emissions; *p*-value for Income Share of Top 10 % (+) is 0.074 and for Income Share of Top 5 % (+) is 0.057; Wald Tests are not statistically significant.

Table 4
Asymmetric regression of total CO_2 emissions for Canada Provinces (long-run effects), 1997 to 2020.

	Top 10 %	Top 5 %
Income Share of Top 10 % (+)	0.676** (0.230)	
Income Share of Top 10 % (−)	0.657ˆ (0.383)	
Income Share of Top 5 % (+)		0.605*** (0.185)
Income Share of Top 5 % (−)		0.434ˆ (0.233)
Long-Run Asymmetry (Wald Test)	0.00	0.32

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, p-values computed using adjusted degress of freedom); N = 240, with 24 observations per province; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts; models control for Gini Coefficient, Total Population, GDP Per Capita, Non-Dependent Population, and Lagged Carbon Emissions; *p*-value for Income Share of Top 10 % (−) is 0.086 and for Income Share of Top 5 % (−) is 0.062; long-run effects estimated with Thombs' user-generated lreff command in Stata; Wald Tests are not statistically significant.

Table 5
Stacked regression of energy and non-energy CO_2 emissions for Canada Provinces (short-run effects), 1997 to 2020.

	Top 10 %	Top 5 %
Income Share Coefficients for Energy Emissions	0.172* (0.057)	0.138* (0.047)
Income Share Coefficients for Non-Energy Emissions	0.207 (0.100)	0.201 (0.103)
Wald Test for Short-Run Income Share (Energy Emissions) = Short-Run Income Share (Non-Energy Emissions)	0.09	0.22

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, *p*-values computed using adjusted degress of freedom); $N = 480$, with 24 observations per province for each emissions outcome; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts; models control for Gini Coefficient, Total Population, GDP Per Capita, Non-Dependent Population, and Lagged Carbon Emissions; Wald Tests are not statistically significant.

Table 6
Stacked regression of energy and non-energy CO_2 emissions for Canada Provinces (long-run effects), 1997 to 2020.

	Top 10 %	Top 5 %
Income Share Coefficients for Energy Emissions	0.670*** (0.191)	0.562*** (0.169)
Income Share Coefficients for Non-Energy Emissions	0.574ˆ (0.308)	0.551ˆ (0.322)
Wald Test for Long-Run Income Share (Energy Emissions) = Long-Run Income Share (Non-Energy Emissions)	0.06	0.01

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, *p*-values computed using adjusted degress of freedom); N = 480, with 24 observations per province for each emissions outcome; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts; models control for Gini Coefficient, Total Population, GDP Per Capita, Non-Dependent Population, and Lagged Carbon Emissions; for Non-Energy Emissions, *p*-value for Income Share of Top 10 % is 0.062 and for Income Share of Top 5 % is 0.087; long-run effects estimated with Thombs' user-generated lreff command in Stata; Wald Tests are not statistically significant.

Table 7
Coefficients for the regression of total CO_2 emissions for Canada Provinces, 1997 to 2020.

	Income share of Top 10 %	Income share of Top 5 %
Inequality	0.233* (0.087)	0.201* (0.081)
Inequality*1998	−0.023 (0.066)	−0.024 (0.055)
Inequality*1999	0.104 (0.063)	0.089 (0.060)
Inequality*2000	0.040 (0.054)	0.031 (0.052)
Inequality*2001	−0.035 (0.065)	−0.042 (0.053)
Inequality*2002	−0.069 (0.088)	−0.078 (0.082)
Inequality*2003	−0.038 (0.061)	−0.035 (0.060)
Inequality*2004	−0.068 (0.073)	−0.064 (0.067)
Inequality*2005	0.004 (0.067)	−0.006 (0.068)
Inequality*2006	−0.060 (0.062)	−0.064 (0.058)
Inequality*2007	−0.112 (0.073)	−0.108 (0.069)
Inequality*2008	−0.041 (0.078)	−0.050 (0.075)
Inequality*2009	−0.130 (0.086)	−0.119 (0.076)
Inequality*2010	−0.055 (0.061)	−0.057 (0.063)
Inequality*2011	−0.154 (0.078)	−0.137 (0.075)
Inequality*2012	−0.034 (0.085)	−0.038 (0.083)
Inequality*2013	0.037 (0.118)	0.017 (0.107)
Inequality*2014	−0.008 (0.099)	−0.025 (0.092)
Inequality*2015	−0.074 (0.082)	−0.079 (0.073)
Inequality*2016	−0.096 (0.097)	−0.094 (0.089)
Inequality*2017	−0.046 (0.113)	−0.054 (0.100)
Inequality*2018	−0.021 (0.109)	−0.035 (0.096)
Inequality*2019	−0.045 (0.102)	−0.055 (0.091)
Inequality*2020	−0.049 (0.110)	−0.051 (0.100)
R-squared within	0.895	0.895

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, p-values computed using adjusted degress of freedom); $N = 240$, with 24 observations per province; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models control for Total Population, GDP Per Capita, Non-Dependent Population, and Lagged Carbon Emissions; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts.

resulting from a 1 % increase in the share of income going to the top 10 %. As the figure shows, the largest increase in emissions occurs in the immediate time period (0.170, which is the short-run effect). By year 10, 94.5 % of the total effect occurs (0.636).

Turning to the control variables, the estimated coefficient for population size is positive and statistically significant, with the exception of Model 2, while the coefficient for GDP per capita is positive and statistically significant in Models 2 and 7, and the coefficient for non-dependent population is positive and significant in Model 5. The coefficients for the economic sector controls in Models 4 through 8 are not statistically significant, while as expected, the coefficient for the lagged dependent variable is positive and significant across all models.

Table 2 reports the same models as in Table 1, but they include the income share of the top 5 % instead of the top 10 %, and the results are very similar (these two income concentration measures are very highly correlated and therefore included in separate models). The income share of the top 5 % has a positive and statistically significant short-run effect on province-level emissions, with point estimates for the elasticity coefficient ranging from 0.122 to 0.148 across the estimated models, which are modestly smaller than for the income share of the top 10 %. The effect of the Gini coefficient remains not statistically significant. The long-run effect of the income share of the top 5 % in Model 3 is 0.563 and statistically significant, meaning that a 1 % increase in the income share of the top 5 % increases CO_2 emissions by 0.563 % over the long run. Fig. 4 illustrates the percentage change in emissions over a 10-year period resulting from a 1 % increase in the share of income going to the top 5 %. As the figure shows, the largest increase in emissions occurs in the immediate time period (0.136, which is the short-run effect). By year 10, 93.7 % of the total effect occurs (0.528).

The table in Appendix 2 reports a series of robustness checks, where models are estimated with the wild cluster bootstrap approach and with Prais-Winsten regression with panel-corrected standard errors.[2] The results are consistent with the analyses presented in Tables 1 and 2, indicating that both the income share of the top 10 % and the top 5 % increase province-level CO_2 emissions, while the estimated effect of the Gini coefficient on emissions is not statistically significant. To assess if the results are sensitive to potential Covid pandemic effects that are not fully accounted for by the time fixed effects, the table in Appendix 3 reports models that exclude observations for the year 2020, and the findings remain very consistent. In analyses available upon request, we exclude Alberta (the province with the highest levels of emissions and the two income concentration measures) and re-estimate the models reported in Table 1 and Table 2, and the results, again, remain very consistent. Overall, the findings of interest appear robust and consistent across different model estimation techniques, are not sensitive to exogenous shocks, most notably the start of the Covid pandemic, and not sensitive to the inclusion of Alberta.

Next, we assess if the short-run and long-run effects of the income share of the top 10 % and top 5 % on province-level CO_2 emissions are asymmetrical, meaning that positive and negative changes in an independent variable differentially affect the dependent variable. Modeling for potential asymmetry in their short-run and long-run effects is important on climate mitigation and overall solutions grounds [64,65]. To do so, and as described in the Methods section, we follow the standard approach to modeling asymmetry by including the positive and negative partial sums of each income inequality measure in the models. The findings are presented in Table 3 (short-run effects) and Table 4 (long-run effects). The results of the Wald tests are all not statistically significant, indicating that there is no asymmetry in the short-run or long-run effects of either of the two inequality measures. In other words, an increase and a decrease in the income share of the top 10 % or the top 5 % result in the same proportional change in CO_2 emissions. Therefore, the initial estimated short-run and long-run effects reported in Table 1 and Table 2 are symmetrical and can be interpreted as the effect of an increase or decrease in income share of the top 10 % or the top 5 % on emissions.

As the next step, we use a stacked regression analysis to test whether the effects of the income share of the top 10 % and top 5 % are different for emissions from the overall energy sector relative to emissions from all other sectors combined (i.e., non-energy emissions).[3] Based on IPCC categorizations, which these data are structured with, energy sector emissions account for the lion's share of emissions for every province. In the analyzed data, they account for between 87.3 % (Ontario) and 99.2 % (Prince Edward Island) of province-level emissions in 1997, and between 86.1 % (Quebec) and 99.3 % (Newfoundland and Labrador) in 2020. While energy sector emissions are the more dominant category for all provinces, using stacked regression allows us to assess if the findings are driven by the relationship between energy emissions and inequality, or if they also apply to other sectors as well. As noted in the Methods section, an advantage of the stacked regression approach is that the coefficients and standard errors are equal to the non-stacked estimates, and a Wald test can be performed to test whether the effects are equivalent or different. The findings are presented in Table 5 (short-run effects) and Table 6 (long-run effects). The results of the Wald tests (all not statistically significant) indicate that the short-run and long-run effects of each income share measure are statistically equivalent for energy and non-energy emissions. In additional analysis available from the lead author upon request, estimated seemingly unrelated regression models lead to the same conclusions.

The analysis thus far indicates that the short-run and long-run effects of income share of the top 10 % and top 5 % on province-level CO_2 emissions are positive, robust to various model specifications and not sensitive to initial Covid pandemic effects, symmetrical, and statistically equivalent for energy and non-energy emissions. As a final step, we assess the extent to which their short-run effects on emissions change in magnitude through time. To do so, we estimate dynamic models, reported in Table 7, that include interactions between the two inequality measures (income share of the top 10 % and top 5 %) and dummy variables for year. The estimated coefficient for the main effect of each inequality measure is for the reference year, 1997. For both, the main effect is positive and statistically significant, with an elasticity coefficient of 0.233 for income share of the top 10 % and 0.201 for income share of the top 5 %. All interactions in both models are not statistically significant, suggesting that the short-run effects of both inequality measures on emissions are temporally stable and do not change in magnitude through time.

4. Conclusion

Income inequality is a topic of substantial and growing interest in research on the climate crisis in general, and in the anthropogenic drivers of emissions literature in particular [1–4,7,73]. Our analysis contributes to this body of interdisciplinary research by focusing on the

[2] The models that serve as robustness checks, reported in Appendix 2, are estimated with the wild cluster bootstrap approach (wildbootstrap fe command) and with Prais-Winsten regression with panel-corrected standard errors (xtpcse command). For the wildbootstrap fe models we specify normal error weights, symmetric *p*-values, and 10,000 replications. The t-statistics are reported for these models as they do not provide standard errors [58,69,70]. Like hc2 clustered robust, wild cluster bootstrap is an approach that is quite suitable for when there are relatively few clusters. The Prais-Winsten regression models estimate panel-corrected standard errors, allowing for disturbances that are heteroskedastic (i.e., each panel has its own variance) and contemporaneously correlated across panels (i.e., each pair of panels has its own covariance) [71,72].

[3] Energy sector emissions consist of those from (1) stationary and (2) transport fuel combustion activities as well as (3) fugitive emissions from the fossil fuel industry. Stationary fuel combustion emission sources include use of fossil fuels by the electricity generating industry, the oil and gas industry, manufacturing industry, and the residential and commercial sectors. Emissions from transport fuel combustion include domestic aviation, road transportation, railways, domestic marine, off-road vehicle use and pipelines. Fugitive emissions associated with the fossil fuel industry are the intentional (flaring) or unintentional releases (leaks or accidents) resulting from production, processing, transmission, and storage of fuels. Non-energy emissions consist of those from (1) industrial processes and product use, (2) agriculture, (3) waste, and (4) land use, land-use change and forestry.

relationship between CO_2 emissions and multiple measures of income inequality in Canada's provinces for the 1997 to 2020 period. To the best of our knowledge, this is the first study to analyze these relationships in a longitudinal, Canadian cross-province context. The Canadian context has global and nontrivial implications, given that Canada is among the world's nations with the highest overall emissions, and Fig. 1 and Fig. 2 highlight the notable differences in emissions and inequality between and within provinces through time.

The results of the statistical analysis indicate that the short-run and long-run effects of income share of the top 10 % and the top 5 % on province-level CO_2 emissions are positive, robust to various model specifications, net of multiple demographic and economic factors, not sensitive to exogenous shocks such as initial Covid pandemic effects, not sensitive to the inclusion of the province with the highest levels of emissions and income concentration, symmetrical, statistically equivalent for energy and non-energy emissions, and their short-run effects do not vary in magnitude through time. The findings also consistently show that the estimated effect of the Gini coefficient on province-level emissions is not statistically significant. Overall, the results underscore the importance in modeling the effects of income inequality measures that quantify different characteristics of income distributions, and they are very consistent with the analytical approaches that suggest that a higher concentration of income is likely to be associated with growth in anthropogenic CO_2 emissions [13,14,16,17,36–41,43,46,47].

From a climate mitigation perspective, the findings underscore the necessity for Canada's provinces to seriously address the role of income inequality, since a high concentration of income towards the top of the distribution appears to be a notable driver of their anthropogenic emissions through time. Based on Model 3 in Table 1 (see also Fig. 3), and using the emissions data included in the reported analysis (see also Fig. 1 and Fig. 2), a 1 % increase in the income share of the top 10 % in the year 2020 would lead to a short-run increase in CO_2 emissions for the provinces combined of 885.124 kt, and a long-run increase in their combined emissions of 3504.05 kt. Regarding the other income concentration measure, based on Model 3 in Table 2 (see also Supplementary Fig. 1), a 1 % increase in the income share of the top 5 % in the year 2020 would lead to a short-run increase in the provinces' combined CO_2 emissions of 708.099 kt, and a long-run increase in their combined emissions of 2931.323 kt. Since the analysis also indicates that the short-run and long-run effects of the income concentration measures are statistically symmetrical, it is reasonable to suggest that decreasing these forms of income inequality could lead to substantial reductions in province-level emissions.

While this study makes distinct and significant contributions, it also has limitations that should be addressed in future research. First, while the findings are consistent with analytical approaches that hypothesize that a higher concentration of income is associated with growth in CO_2 emissions, the reported analysis, based on current data availability, do not include measures that fully capture the underlying mechanisms tied to power, overconsumption, and status competition that are proposed to shape the emissions and inequality relationship. We hope to address this limitation in future research, as doing so has implications for climate mitigation action and policy, as well as for more nuanced hypothesis testing and theory refinement. Second, due to current data availability, the reported analysis covers the 1997 to 2020 period. Future research would do well to also include years post 2020 to assess if the effects of income inequality on province-level emissions remained consistent or shifted in magnitude in more recent years. Third, while the analysis focuses on provinces, it overlooks potential variation between smaller geographic units within provinces. Future research, data permitting, would do well to assess the effects of income inequality on emissions within Canada at even smaller scales. Fourth, while we find that none of the economic sector measures suppress the estimated effects of the income concentration measures, nor do they exert significant effects on carbon emissions themselves, future research should consider if the structure of economic sectors and industries shape income inequality within and across provinces, as well as if economic elites in some provinces have benefited from fossil capitalism in ways that shape their political power and the overall relationship between emissions and inequality [74]. Fifth, future research should also assess the effects of income inequality on province's consumption-based (i.e., adjusted for trade) emissions, if and when such data become available. Finally, it is unclear if the findings are widely generalizable outside of Canada. While prior longitudinal research yields similar results for U.S. states [16], future research would do well to conduct similar analysis in other subnational contexts.

Code availability

All Stata commands used in the analysis are available upon reasonable request from the lead author and will be publicly available on their lab's website.

CRediT authorship contribution statement

Andrew Jorgenson: Writing – review & editing, Writing – original draft, Supervision, Investigation, Formal analysis, Conceptualization. **Taekyeong Goh:** Writing – review & editing, Formal analysis, Data curation. **Ryan Thombs:** Writing – review & editing, Formal analysis, Conceptualization. **Yasmin Koop-Monteiro:** Writing – review & editing, Conceptualization. **Mark Shakespear:** Writing – review & editing, Conceptualization. **Grace Gletsu:** Writing – review & editing, Conceptualization. **Nicolas Viens:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

Appendix 1. Univariate descriptive statistics

	Mean	Std Dev	Skewness	Kurtosis
Total CO_2 Emissions	56,011.57	63,006.91	1.32	3.38
Energy Emissions	51,685.00	57,709.06	1.38	3.64
Non-Energy Emissions	4326.57	6214.17	1.54	4.22
Income Share of Top 10 %	25.29	8.54	0.87	2.85
Income Share of Top 5 %	16.1	6.59	1.19	3.74
Gini Coefficient	0.30	0.02	−0.27	2.93
Total Population	3,348,572.00	3,949,318.00	1.46	4.02
GDP Per Capita	47,059.30	13,352.74	0.93	2.76
Non-Dependent Population	67.83	1.88	−0.34	2.31
Manufacturing as % GDP	9.56	4.02	0.55	3.17
Agriculture as % GDP	3.44	2.37	1.19	3.47
Services as % GDP	66.79	11.24	−0.77	2.02

(continued on next page)

(*continued*)

	Mean	Std Dev	Skewness	Kurtosis
Energy as % GDP	2.09	0.89	0.61	2.33
Fossil Fuels as % GDP	6.97	10.71	1.39	3.74

Notes: Std Dev = standard deviation; all variables are converted into logarithmic form prior to analysis; $N = 240$.

Appendix 2. Coefficients for the regression of total CO_2 emissions for Canada Provinces, 1997 to 2020

	WCB	WCB	PCSE	PCSE
	Model 1	Model 2	Model 1	Model 2
Income Share of Top 10 %	0.170*		0.175***	
	[3.63]		(0.052)	
Income Share of Top 5 %		0.136*		0.138***
		[3.57]		(0.041)
Gini Coefficient	−0.177	−0.172	−0.174	−0.168
	[−1.33]	[−1.35]	(0.107)	(0.106)
Total Population	0.387**	0.351**	0.408***	0.365***
	[4.66]	[4.21]	(0.100)	(0.096)
GDP Per Capita	0.179ˆ	0.179ˆ	0.191ˆ	0.188ˆ
	[2.55]	[2.73]	(0.114)	(0.113)
Non-Dependent Population	0.834	0.900	0.870**	0.922**
	[1.95]	(2.23)	(0.318)	(0.311)
Lagged Carbon Emissions	0.748***	0.758***	0.731***	0.746***
	[21.49]	[23.38]	(0.054)	(0.051)
R-squared			0.999	0.999

Notes: WCB models estimated with wild cluster bootstrap in Stata (wildbootstrap xtreg, 10,000 replications, ptype symmetric, error weight normal); PCSE models estimated Prais-Winsten regression in Stata (xtpcse, panel-corrected standard errors, AR[1] correction).
N = 240, with 24 observations per province; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); t statistics for WCB models in brackets; panel-corrected standard errors for PCSE models in parentheses; WCB models include province-specific fixed effects derived from the within estimator; PCSE models include province-specific intercepts; all models include unreported year-specific intercepts.

Appendix 3. Coefficients for the regression of total CO_2 emissions for Canada Provinces, 1997 to 2019

	Model 1	Model 2
Income Share of Top 10 %	0.172*	
	(0.050)	
Income Share of Top 5 %		0.141*
		(0.042)
Gini Coefficient	−0.179	−0.175
	(0.169)	(0.162)
Total Population	0.366*	0.327*
	(0.097)	(0.101)
GDP Per Capita	0.178	0.180
	(0.104)	(0.094)
Non-Dependent Population	0.717	0.789
	(0.525)	(0.490)
Lagged Carbon Emissions	0.748***	0.757***
	(0.029)	(0.026)
Long-Run Effects for		
Income Share of Top 10 % (Model 1)	0.684***	0.578***
Income Share of Top 5 % (Model 2)	(0.190)	(0.172)
R-squared within	0.860	0.860

Notes: models estimated with xtreg fe in Stata 18 (hc2 clustered robust standard errors, *p*-values computed using adjusted degress of freedom); $N = 230$, with 23 observations per province; non-binary variables are in logarithmic form; ***$p < .001$ **$p < .01$ *$p < .05$ ˆ$p < .10$ (two-tailed); hc2 clustered robust standard errors in parentheses; all models include province-specific fixed effects derived from the within estimator and unreported year-specific intercepts; long-run effects estimated with Thombs' user-generated lreff command in Stata.

Data availability

The data that support the findings of this study are available upon reasonable request from the lead author and will be publicly available on their lab's website.

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