Understanding the Relationship Between Income Inequality and Carbon Dioxide Emissions: The Canadian Context

by

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Abstract

This thesis examines the evolution of income inequality in Canada from 1997 to 2019 through the Gini coefficient and the share of income of the top 10% of income earners. These metrics are then used to evaluate whether there are any associations between income inequality and CO_2 emissions. The results reveal that the Gini coefficient is negatively associated with CO_2 emissions; however, no definitive conclusions can be drawn about the effect of income share. The implications of the results for the effect of economic policies (i.e., redistributive) on national climate commitments are then discussed.

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Dedication

To my parents, for all their constant support and guidance.

1. Introduction

Economic inequality and anthropogenic climate change are two of the most serious challenges facing the world in the 21st century. The release of greenhouse gases (GHGs) into the atmosphere is warming the planet, resulting in more frequent and destructive environmental events (e.g., hurricanes, flooding, fires), fatalities due to heat exposure, and biodiversity loss (Clarke et al., 2022; Bellard et al., 2012; Arneth et al., 2020; Denchak, 2016). Consequently, most of the research on economic inequality and climate change has focused on how climate change will exacerbate existing inequalities indicating the outsized impact of climate change on marginalized and at-risk demographic groups (Hamann et al., 2018). Low-income individuals are more likely to be exposed to the consequences of natural disasters, some of which may increase in severity with climate change (Hamann et al., 2018). For example, poorer individuals are less able afford air-conditioning and home insurance which would help them deal with the impacts of heat waves and hurricanes (Flemming et al., 2018; Alizadeh et al., 2022; Hamann et al., 2018).

Beyond its impact on the ability of individuals to cope with the damaging effects of climate change, economic inequality has been identified as a pressing issue that holds implications for the health of economies and polities (Hamann et al., 2018). Although there are multiple ways to measure economic inequality, income inequality represents a particular concern given the fact income inequality has increased in many regions of the world since the 1980s (Piketty, 2020). At the global level from 1980 to 2018 the bottom 50% of income earners obtained just 12% of economic growth while the top one per cent obtained 27% (Piketty, 2020). Moreover, at the country level, economic growth has tended to be highly unequal, with a small number of very productive regions making an outsized contribution to national growth (OECD, 2019). This regionally imbalanced nature of economic growth within countries has led to inter-regional inequality which has, in turn, produced social and political unrest (OECD, 2019).

Two of the most commonly used measures of income inequality are the Gini coefficient – which is derived from the Lorenz curve – and income shares decomposed into deciles. The Lorenz curve is a graphical illustration of income inequality that plots a percentage of total income or wealth earners on the x-axis and their share of total income or wealth within a jurisdiction on the y-axis, with a 45 degree line typically used represent perfect income equality in an area (i.e., x = y) (Trapeznikova, 2019). Consequently, a Lorenz curve that 'curves' below the 45 degree line is indicative of income inequality (Trapeznikova, 2019). Based on the Lorenz curve, the Gini coefficient "…is defined as the area between the Lorenz curve and the 45-degree line, dived by the total area under the 45 degree line" (Trapeznikova, 2019, p.66) (see Figure 1). The measure takes values between 0 and 1 with zero meaning total income equality and one meaning that one individual has captured all income within an area (Trapeznikova, 2019). Conversely, the share of income metric represents the amount of income within an area that is obtained by members of a specific income group (Statistics Canada, 2022a). In comparison to the Gini coefficient, the share of income metric can be easier to interpret (Trapeznikova, 2019). However, income share can miss important nuances between percentiles, as well as above and below certain cut off points. For example, if income share is expressed using deciles, the income shares of the top 10% of the income distribution will necessarily obscure differences between the upper 1% of income earners and the rest of the top 10%. Between the two measures, the Gini coefficient tends to be more stable over time while there can be more movement in the decile method (Fixler et al., 2020). Additionally, the Gini coefficient tends to be more influenced by changes in the middle of the income distribution (De Maio, 2007; Hailemariam et al., 2019).

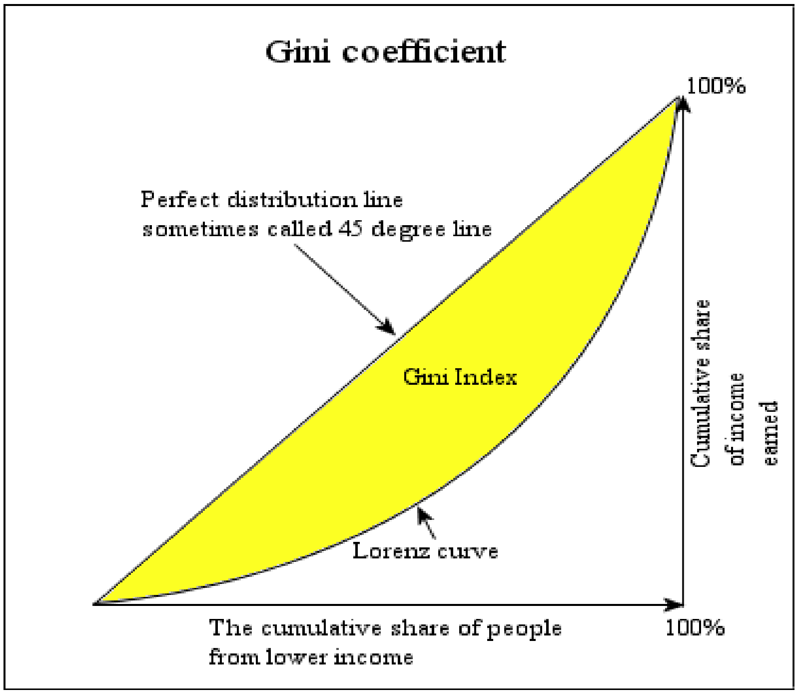

Figure 1. Graphical illustration of the Lorenz Curve and the Gini Index. Source: Bluemoose (2020)

In Canada, income inequality has increased over the last 37 years. From 1982 to 2019, the share of income received by the top 10% of income earners increased from 30% to 34% (Statistics Canada, 2022a). However, much of this increase happened from 1990 to 2000 due to structural changes in the economy and government policies after which the income share has remained relatively stable (Statistics Canada, 2022a; Green et al., 2017). Some of the rise in income inequality has been attributed to technological change, the growing importance of computers in society, and automation which has rewarded some workers and negatively impacted others (Green et al., 2017). The Gini coefficient tells a relatively similar story, with the coefficient increasing from 0.388 in 1982 to 0.421 in 2019 (Statistics Canada, 2022b). Much like the share of income, the bulk of the increase was from 1990 to 2001 after which the measure stabilized (Statistics Canada, 2022b). When looking at the tax adjusted Gini coefficient there has been a clear downward trend between 2015 and 2019, with the coefficient just 0.10 points off of its 1982 levels (Statistics Canada, 2022b). This means that after-tax income inequality in Canada went down slightly between 2015 and 2019, likely due to an increase in national economic redistribution. It should be noted that these aggregate trends at the national level mask substantial variation at the provincial level. For example, in Alberta the share of income received by the top 10% of income earners increased from 40% in 1982 to 44% in 2019, reaching as high as 52% in 2015 (Statistics Canada, 2022a). Meanwhile, the share of income received by the top 10% of income earners in Nova Scotia increased from 20% to 21% with a high of just 22.2% (Statistics Canada, 2022a). Beyond the effect of inter-regional inequality on political unrest and disaffection (Dijkstra et al., 2020; Lenzi & Perucca, 2021), changes in the levels of inequality in each province and the differences between them could potentially be of interest from a policy perspective if higher levels of inequality are associated with higher levels of emissions.

Given the salience of both income inequality and climate change, it is important to understand the linkages and potential tensions between these two issues. Indeed, while previous studies indicate that there are a number of different drivers of GHG emissions including gross-domestic product (GDP) growth, population growth, and urbanization (Rosa & Dietz, 2012; Haberl et al., 2020; O'Neill et al., 2012; Blanco et al., 2014), the relationship between income inequality and carbon dioxide equivalent (CO_2) emissions is less clear. Previous research about this topic has achieved inconsistent results, possibly due to the use of different models and measures of income inequality. Specifically, past studies using the Gini coefficient have achieved mixed results. Similarly, studies that have employed the income share metric have achieved a variety results, with two studies that used the income share of the top 10% finding a positive relationship (Jorgenson et al., 2017, Hailemariam et al., 2019) with another finding a negative relationship (C. Liu et al., 2019). Hailemariam et al. (2019) have claimed that the two measures of inequality may capture separate theoretical mechanisms linking inequality and CO_2 emissions.

Consequently, this paper aims to provide more clarity in the academic understanding of how income inequality and CO_2 emissions may be linked (if at all). The specific objectives are to: (1) assess and compare levels of income inequality in Canadian provinces from 1997 to 2019 using the Gini coefficient and the income share of the top 10% earners, and (2) assess the relationship between income inequality and CO_2 emissions in 1997-2019 using both measures of inequality. The paper begins with a brief summary of the existing literature on the relationship between CO_2 emissions and income inequality before proceeding to outline its theoretical framework and methodology. The study finishes with a discussion of the results and their implications for policy-making such as the tensions between efficiency, the polluter pays principle, and the ability to pay principle.

2. Literature review: Past relationships between income inequality and CO_2 emissions

Several empirical studies have examined the relationship between economic inequality and CO_2 emissions using an ex-post approach; however, many of them achieved inconsistent results. Using the Gini coefficient and the share of income captured by the top 10% of income earners, Jorgenson et al. (2017) examined the relationship between economic inequality and CO_2 emissions at the state level in the United States in 1997-2012. In nearly all models employed in the study, the share of income captured by the top 10% was found to be significant in predicting higher levels of CO_2 emissions while the Gini coefficient suggesting that these two measures of income inequality may give rise to different results. While the study provides useful insights within the context of the United States (US), the authors suggest that future studies examine the relationship between income inequality and emissions within other sub-national jurisdictions to validate their results. In contrast, Cenjie Liu et al. (2019) found that income inequality measured through the income share of the top 10% has a positive short-term relationship and a negative long-term relationship with CO_2 emissions across US states using data from 1997- 2015.

Qianqian Liu et al. (2019) studied income inequality in China via Global Moran's I which captures the spatial distribution of income and the Gini coefficient. In both cases, they found income to be positively associated with CO_2 emissions, with Global Moran's I having a larger influence on CO_2 emissions than the Gini coefficient. The authors explain that the concentration of income within certain areas of a region may impact the distribution of its CO_2 emissions (Q. Liu et al., 2019). Similarly, using a sample of 158 countries between 1980 and 2018, Grunewald et al. (2017) found a negative association between income inequality and CO_2 emissions for lower income to middle countries, and a positive association for upper-middle income and higher income countries. They explained that in lower income countries, decreasing levels of income inequality may cause increasing numbers of individuals to consume energy intensive goods and services. Baležentis et al. (2020) found that income inequality tends to lead to higher carbon footprints, up to Gini coefficient levels of 30, highlighting the importance of redistributive fiscal policies.

In contrast to some of the more recent studies, Uddin et al. (2020) revealed that economic inequality (measured via Gini coefficient) and CO_2 emissions had a positive relationship between 1870 and 1880, but a negative relationship between 1950 and 2000, and then a non-significant relationship between 2000 and 2014 within the G7 countries. The authors explain that post-war demand-side economic policies gave lower income households the ability to purchase energy intensive goods which contributed to rising emissions since this demographic group has a larger marginal propensity to emit than their higher income counterparts. Relatedly, the reduced bargaining power of labour between 1975 and 2000 led to growing inequality which in turn contributed to the observed negative relationship between inequality and emissions. The authors also suggested that growing income inequality encouraged wealthy members of the population to amass capital which led to the development of more energy efficient products, contributing to relative decreases in emissions. Similarly, using panel data from 92 countries, Huang & Duan (2020) found income inequality to have a negative relationship with CO_2 emissions and energy intensity in 1991-2015.

Finally, employing a sample of G20 countries from 1988 to 2015, Chen et al. (2020) found income inequality – measured through the Gini coefficient – to have no relationship with CO_2 emissions in developed countries apart from countries that have reasonably high per capita CO_2 emissions (where the impact is negative) and to have a positive impact on CO_2 emissions in emerging economies. They suggest that this may be because high levels of inequality may hamper innovation in environmentally friendly technologies which could lower CO_2 emissions.

Relative to previous research, this study is geographically unique as no previous studies have focused solely on Canada at a national or provincial level. Although the G20 countries have been studied collectively (Chen et al, 2020), no study has focused on a country with the emissions profile of Canada, with the arguable exception of those that have focused on the United States. Amongst relatively affluent nations, Canada has a high per-capita lifestyle and consumption related carbon footprint (Akenji et al., 2021; Ivanova et al., 2015). However, according to Nolan et al. (2019) Canada has ranked in the middle of the pack amongst developed countries in terms of changes in income inequality since 1980. This sets Canada apart from other developed countries with similarly high per-capita emissions such as Australia, the United Kingdom, and the United States (which has been studied previously) (Ivanova et al., 2015). Additionally, it bears mentioning that although acceptable levels of inequality will vary based on a country's political and social preferences, income inequality has been identified as an important issue facing many countries in the 21st century that holds implications for political, social (Edelman, 2020), and public health outcomes in a society (Bor et al., 2017). Furthermore, linkages between income inequality and CO_2. emissions could hold implications for the values that many citizens consider to be significant in the creation of climate policy such as efficiency, the polluter pays principle, and the ability to pay principle (Dietz & Atkinson, 2010). Efficiency can be defined as the extent to which a policy achieve its goals and its overall price-tag (Dietz & Atkinson, 2010) while the polluter pays principle can be defined as the idea that those most responsible for pollution pay the majority of the costs associated with addressing with it (Dietz & Atkinson, 2010; Grantham Research Institute on Climate Change and the Environment at the

LSE, 2022). The ability to pay principle implies that those with the greatest ability to handle the costs that stem from combating pollution contribute the most to tackling it (Dietz & Atkinson, 2010; Massenberg, 2021).

It should also be noted that nearly all previous studies that have examined the impact of income inequality on emissions have utilized aggregated data, with even those that employ sub-national data using data aggregated at the regional, state, or provincial level. Past research has suggested that there are number of factors that can impact the level of CO_2 emissions of a household including income, location of residence (i.e., rural or urban), and household size (Büchs & Schnepf, 2013, Pang et al., 2019; Oswald et al., 2020). The use of highly aggregated data in this study as well as in previous research is mostly due to the absence of available disaggregated data. The aggregated data may obscure the effect of location on CO_2 emissions, which represents an important area for future research. Indeed, Pang et al. (2019) demonstrate rural households in Switzerland to be associated with greater levels of direct CO_2 emissions and urban households to be associated with higher levels of indirect emissions while Büchs & Schnepf (2013) reveal rural households in the UK to be associated with greater levels of CO_2 emissions.

3. Theoretical framework

Previous studies used three main frameworks to explain a potential relationship between income inequality and emissions ranging from the marginal propensity of different demographic groups to emit, to consumption competition, to the political influence of the wealthy. The marginal propensity to emit describes the extent to which different income groups change their consumption in response to changes in their incomes while consumption competition refers to the notion that an increase in incomes amongst wealthy individuals will lead to higher CO_2 emissions through status-related consumption. Political influence of the wealthy is the theory that higher levels of income inequality will lead to increased CO_2 emissions via wealthy individuals engaging in lobbying or activism that obstructs efforts to address environmental issues. Table 1 outlines the scale and driver of each framework.

Table 1. Drivers and scale of the theoretical frameworks

Framework name	Driver	Scale
Marginal propensity to emit	Income elasticities	Individual decisions which collectively impact CO_2 emissions
Consumption competition	Status driven consumption patterns	Individual decisions which collectively impact CO_2 emissions
Political influence of the wealthy	Wealth translated into political influence (e.g., lobbying)	Influence over the direction of national or provincial laws, institutions, and policies

This study builds on frameworks of the marginal propensity of different groups to emit and consumption competition. A negative relationship between income inequality and emissions will be taken as an indication of the marginal propensity of different groups to emit while a positive relationship will be taken as an indication of the consumption competition theory. The two main variables used to test these competing frameworks are the Gini coefficient and the share of income within a geographic area received by the top 10% of income earners. The rationale behind the selection of these variables is outlined in the next section.

Prior studies suggested that inequality and emissions may be associated by the marginal propensity of different individuals to emit (Jorgensen et al., 2017; Uddin et al., 2020; Grunewald et al., 2017) which is the first theoretical framework tested in this study. The literature suggests that the marginal propensity to emit should decline with income for two reasons (Jorgensen et al., 2017; Uddin et al., 2020; Grunewald et al., 2017). First, environmental-friendly products tend to be fairly expensive, making it more likely that lower income households utilize emissions intensive products (Uddin et al., 2020). In fact, income has been found to be positively associated with the readiness of households to purchase energy efficient technology with the exception of lightbulbs, solar panels, and heat pumps (Amel & Brandt, 2015). Second, a Keynesian economic model posits that lower income individuals have a higher marginal propensity to consume than higher income individuals (Jorgensen et al., 2017; Uddin et al., 2020). Put differently, lower income earners will consume more than higher income earners in response to changes in their income (i.e., lower income earners have larger income elasticities) (Sampedro et al., 2021). This is because, on average, lower income earners will derive more personal utility or satisfaction from increasing their levels of consumption whereas higher income earners are much closer to achieving their maximum levels of contentment with their current consumption levels (Sampedro et al., 2021). Accordingly, increasing the amount of economic inequality will lower emissions because income is transferred to the individuals with a lower marginal propensity to consume (Jorgensen et al., 2017; Uddin et al., 2020).

However, other sociological and economic theories have predicted higher levels of economic inequality to result in increased levels of emissions. Indeed, Veblen’s ideas around consumption predicts that higher income inequality will lead to higher levels of consumption competition (Jorgensen et al., 2017; Uddin et al., 2020). According to this theory, the consumption behaviours that are considered to be desirable are defined by the highest income individuals and households which are then emulated by others (Jorgensen et al., 2017; Uddin et al., 2020). This causes increased expenditures on emissions intensive products (Jorgensen et al., 2017; Uddin et al., 2020). In other words, higher income inequality encourages individuals to lead increasingly emissions intensive lifestyles in order to signal their value and status through their purchases (Stewart, 2021). This theoretical linkage between income inequality and emissions describes the second theoretical framework used in the study, the consumption competition hypothesis.

Empirical evidence has generally confirmed a positive relationship between income and emissions, although some research paints a more complicated picture. Using geodemographic data, Baiocchi et al. (2010) examined emissions that are directly related to the lifestyle of consumers as well as those arising from products purchased by them, demonstrating that income is positively associated with emissions. Based on the findings of Ivanova et al. (2017), higher income households can be expected to spend more money on mobility, clothing, and manufactured products than comparatively lower income households. At a global level, the top 10% of income earners are far more likely to purchase recreational items, package holidays, and vehicles (Oswald et al., 2020). Similarly, Girod & de Haan (2009) found that within Switzerland, mobility accounted for a large portion of the difference between high emitters and low emitters, with the latter typically spending their spare time doing recreational activities that are associated with fewer emissions (i.e., going to the movies). Within the UK, transport related emissions of upper income earners have been estimated to be 3.5 times that of those in the bottom income bracket (Brand & Boardman, 2008). Conversely, research has suggested that higher levels of economic inequality can translate into lower homeownership rates which may increase the amount housing held by private landlords (Galvin & Sunikka Blank, 2018). Units operated by private landlords have been shown to have lower thermal performance than dwellings owned by individual households which could produce higher CO_2 emissions over time (Galvin & Sunikka Blank, 2018). Furthermore, lower income households have been shown to be less likely to purchase energy saving technology largely due to their cost (Galvin & Sunikka Blank, 2018), a phenomenon which could be exacerbated by increases in income inequality. This research on dwelling related CO_2 emissions underscores the idea that households do not always consciously control their carbon footprint and that they are, to some degree, a product of the social, economic, and cultural systems in which people are embedded. For instance, the transport related carbon footprint of different income earners may depend on whether their neighbourhood is located on the outskirts of town or close to the city center, a factor that is dependent upon the cost of living, where affordable housing is available, and the location of 'desirable' neighbourhoods (Wachsmuth et al., 2016; Baiocchi et al., 2010)--phenomena that are rarely within a household's control.

Beyond lifestyle related factors, it is also possible that higher levels of income inequality may lead to political outcomes that cause CO_2 emissions to rise. Past research has suggested that higher levels of inequality may give wealthy members of society that are opposed to climate action large amounts of influence (Jorgenson et al., 2017; Uddin et al., 2020). This influence could be exercised in multiple ways ranging connections to and more frequent discussions with electoral officials, to the ability to set the political agenda through the ownership of various media outlets and think tanks (The Economist, 2018). There is also evidence to suggest that high levels of economic inequality may produce electoral outcomes that carry negative implications for climate action. In a 2021 study, Lübke (2021) found climate denial to be elevated amongst individuals that face labour market insecurity and feel a lack of control over their economic prospects. It is possible that these individuals may feel be more inclined to support populist politicians who are actively against or do not strong take strong stance on addressing climate change (Colmer & Stern, n.d.). Preliminary evidence for these types of political forces may be seen in the yellow-vest movement in France (Colmer & Stern, n.d.).

Hailemariam et al. (2019) claim that different measures of income inequality may capture different effects of the phenomenon on emissions. For example, they suggest that the Gini coefficient may better represent the framework that centers around the marginal propensity of different individuals to emit due to its tendency to be influence by changes in the middle of the income distribution while the income share may better represent the political economy or consumption competition hypothesis.

4. Methods

4.1. Data collection

The dependent variable included in the study is provincial CO_2 emissions while the primary independent variable of interest, income inequality, is measured through the Gini coefficient and the share of income obtained by the top 10 % of income earners in each province. The major covariates in the study are provincial GDP and population, as well as the combined contribution of the mining, quarrying, oil, and gas sectors (MQOG) to each provincial economy. The choice of independent variables was motivated by a range of considerations including the potential impact of each variable on CO_2 emissions, to the inclusion of these variables in previous studies, to the ability to model the effect of each independent variable (Table 2).

Table 2. Variables hypothesized to be associated with CO_2 emissions

Variable	Hypothesized sign of association	References
Gini coefficient	Positive	Baek & Gweisah (2013) (short & long-run), Zhang & Zhao (2014), Hao et al. (2016) (nationwide & one model for non-eastern region), Q. Liu et al. (2019), Balžentis (2020), Demir et al. (2019) (short-run), Grunewald et al. (2017) (upper middle to high income countries), Uddin et al. (2020) (1870-1880), Chen et al. (2020) (quantile dependent)
	Negative	Heerink et al. (2001), Demir et al. (2019) (long-run), Huang & Duan (2020), Brânnlund & Ghalwash (2009), Hailemariam et al. (2019), Hübler (2017), Coondoo & Dinda (2008) (high income countries), Grunewald et al. (2017) (low to middle income countries), Uddin et al. (2020) (1950-2000), Chen et al. (2020 (quantile dependent), Hao et al. (2016) (one model for non-eastern region), Ali et al. (2016)
	No association	Wolde-Rufael & Idowu (2017), Jorgenson et al. (2017), Coondoo & Dinda (2008) (low income countries), Uddin et al. (2020) (2000-2014), Knight et al. (2017), Hao et al. (2016) (eastern region), Ali et al. (2016)

Variable	Hypothesized sign of association	References
Income share of top 10%	Positive	Jorgenson et al. (2017), Hailemariam et al. (2019) (by itself), C. Liu et al. (2020) (short-run)
	Negative	C. Liu et al. (2020) (long-run), Hailemariam et al. (2019) (when interacted with GDP)
	No association	Kasuga & Takaya (2017)
Wealth share of top 10%	Positive	Knight et al. (2017)
Income inequality	Positive	Not available
	Negative	Ali et al. (2016)
Income share top 20%	Positive	McGee & Greiner (2018) (when interacted with GDP)
	Negative	McGee & Greiner (2018) (by itself)
GDP	Positive	McGee & Greiner (2018), Q. Liu et al. (2019), Baležentis et al. (2020), Chen et al. (2020), Huang & Duan (2020), Uddin et al. (2020), Grunewald et al. (2017), Demir et al. (2019) (long-run), Ali et al. (2016), Hailemariam et al. (2020), Knight et al. (2017), Jorgenson et al. (2017), Chen et al. (2020) (quantile dependent), Balžentis (2020), Uddin et al. (2020), C. Liu et al. (2019) (panel quantile)
	Negative	McGee & Greiner (2018), Chen et al. (2020) (quantile dependent), Demir et al. (2019) (short-run), Hao et al. (2016), Balžentis (2020), C. Liu et al. (2019) (long-run), Baek & Gweisah (2013) (short & long run)
	No association	Ali et al. (2016), Hailemariam et al. (2020), C. Liu et al. (2019) (short-run)
Population	Positive	Hailemariam et al. (2020), Jorgenson et al. (2017)
	Negative	Hailemariam et al. (2020)
	No association	Hailemariam et al. (2020), Jorgenson et al. (2017)
Mining, Quarrying, Oil, and Gas Share of GDP	Positive	Jorgenson et al. (2017) (fossil fuel production)
	Negative	Not available
	No association	Jorgenson et al. (2017) (fossil fuel production)
GDP^2	Positive	Chen et al. (2020) (quantile dependent), Demir et al. (2019) (short-run), Hao et al. (2016), Balžentis (2020)
	Negative	Q. Liu et al. (2019), Huan & Duan et al. (2020), Grunewald et al. (2017), Demir et al. (2019) (long-run), C. Liu et al. (2019) (panel quantile), Hailemariam et al. (2020), Chen et al. (2020) (quantile dependent), Uddin et al. (2020)

Variable	Hypothesized sign of association	References
	No association	McGee & Greiner (2018), Hailemariam et al. (2020), C. Liu et al. (2019) (short-run)

While there is a general positive relationship between industrialization and CO_2 emissions (Grubb et al., n.d.), the connection between GDP and CO_2 emissions is subject to more debate. Historically speaking, GDP and CO_2 emissions were tightly coupled together (Hughes & Herian, 2017; Haberl et al., 2020; Hausfather, 2021) while in recent years evidence of absolute decoupling of economic growth from emissions in certain economies has emerged (Hausfather 2021). The concept of an Environmental Kuznets Curve (EKC) suggests that the initial periods of economic development will be associated with increases in environmental damage due to the need to meet basic needs (i.e., industrialize) using the cheapest possible resources such as fossil fuels (Stern, 2004). But in the later periods, the EKC suggests there will be associated decreases in environmental destruction due to changing social and political priorities for higher environmental quality (Stern, 2004). While Saqib & Benhmad's (2020) meta-analysis of the studies on the EKC found substantial evidence of its existence, Wiedmann et al. (2020) asserted that there is no proof of its existence when a consumption-based emissions accounting approach is used. Due to the fact that decoupling of growth from emissions has not been uniform across Canadian provinces (Hughes & Herian, 2017; Canadian Institute for Climate Choices, 2020), GDP is included in the study as a covariate.

Historical evidence suggests that population growth acts as a driver of GHG emissions (O'Neill et al., 2012; Blanco et al., 2014; Rosa and Dietz, 2012) and is projected to do so in the future (Kruse-Andersen, 2020). For this reason, population is included in the study as a covariate.

To account for the different role that MQOG industries play across different provinces, the combined contributions of the MQOG sectors to each provincial economy are included as co-variates. This approach resembles the approach taken by Jorgensen et al. (2017) who control for state fossil fuel production. Similarly, other studies in this area have controlled for the impacts of various sectors of the economy on CO_2 emissions. For example, Halemariam et al. (2020) and Uddin et al. (2020) control for the effects of the share of agriculture in economic output. In Canada, the presence of the oil and gas sectors gives rise to significant differences in per-capita emissions across provinces. Two of the provinces with among the highest GHG per capita emissions in Canada are Alberta and Saskatchewan, largely due to the prominence of the oil gas sectors in each province (Anderson, 2022; Conference Board of Canada, n.d.).

All data was public and obtained from Statistics Canada (2022a, 2022b, 2022c, 2022d, 2022e) or Environment and Climate Change Canada (2022a). The data source for income share is Statistics Canada's high income tax filter which is itself a product of the Longitudinal Administrative Databank (LAD) (Statistics Canada, 2022a, 2022f). This data is updated annually to provide recent information abound income and demographics in Canada (Statistics Canada, 2022f). The main source of data on income is the T1 tax returns received by Statistics Canada every year (Statistics Canada, 2022f). The data source on CO_2 emissions is Environment and Climate Change Canada's (2022a) Official Greenhouse Gas Inventory. Canada submits its GHG inventory each year to the United Nations Framework Convention on Climate according to their reporting guidelines (Environment and Climate Change Canada, 2022a). Data on GDP, population, income share, the Gini coefficient, and CO_2 emissions were all unaltered in analysis while the share of the MQOG sectors in each provincial economy were derived by dividing the absolute amount each contributed to GDP at basic prices in each year from 1997 to 2019 by total

GDP at basic prices. These datasets were eventually combined to create two panel datasets which can be found in Appendix B. Territories were excluded from the study due to limitations on data availability. Ideally, data on settlement type (i.e., rural, urban, remote) or rates of urbanization would have been included in the study but limitations on data availability from Statistics Canada prevented this. The years under consideration were selected based on the availability of data since information on the MQOG sectors' contribution to provincial GDP was only available from 1997 onwards.

4.2. Descriptive statistics for the studied variables

Descriptive statistics for the studied variables are displayed across all of the measurement occasions for 1997-2019 in *all* provinces in Table 3. Additional tables showing descriptive statistics for every variable measured in each *individual* province can be found in Results in Table 4.

Table 3. Descriptive statistics for studied variables in 1997-2019

Variable	Mean	Median	Standard deviation	Min	Max
CO_2 emissions ($ktCO_2$)	57	30	64	1	225
Total GDP (Billions chained 2012 dollars x1,000,000,000)	127	44	151	4	636
Population (1000s of people x1,000)	3330	1145	3925	136	14545
Mining, quarrying, oil, and gas GDP contribution to total GDP	0.1	0.035	0.133	0.0002	0.498
Gini Coefficient	0.4	0.429	0.023	0.391	0.503
Income share of the top 10%	29	26	8	16	52

CO_2 emissions had a mean of 56 $MtCO_2$ and a median of 29 $MtCO_2$ from 1997 to 2019 across all units while GDP had a mean of $127 and a median of $44. On average the MQOG sector made up approximately 11% of a province's economic output while the median amount was about 3.5%. Additionally, the Gini coefficient had a mean value of 0.430 and a median of 0.429 while the share of income received by the top 10% of income earners had a mean of 29% and a median of 26% implying that there was more variation in the values taken by the latter during the time period under study. Throughout the time period under examination, the average number of people living in Canadian provinces was 3.3 million while the median was 1.1 million.

The minimum and maximum values for each variable demonstrate the wide variation in values that the different variables within the study take over time and space. The combined share of the mining, quarrying, oil, and gas sectors in a province's economic output (their combined contribution to GDP) ranged from as little as 0.00022 (rounded ratio) to comprising nearly half of a province's economic productivity. Income share ranged from a low of 16% to a high of 52% while the Gini coefficient ranged from a low of 0.391 to a high of 0.503.

4.3. Data analysis

The majority of data cleaning, the generation of visualizations, and the transformation of the data into a single panel data set was performed using R and Python using guidance and training documentation from Wickham et al. (2021), Waskom (2021), Story & Fernandes (2021), and OpenStreetMap (n.d.). The code used for these tasks can be found in the files attached in Appendix C.

To address objective 1, descriptive statistics and frequency distribution figures are used to help assess the evolution of income inequality across Canadian provinces. To examine the variation in income inequality when measured using both the Gini coefficient and income share across Canadian provinces one-way ANOVA tests are employed, with pairwise t-tests that use Holm's *p*-value adjustment reported below (Navarro, 2019).

To assess the potential association between income inequality and CO_2 emissions (objective 2), fixed and random effects models are used to examine variables that change across time and units, known as time-series cross-sectional data (Bell & Jones, 2015; Fortin-Rittberger, 2015; Urdinez, 2021). Random effects hold the advantage of being able to measure variance between units since these estimators use a combination of within and between unit variance to estimate their coefficients (Firebaugh et al., 2013; Bell & Jones, 2015). In these models, the unit level effects terms represent unit specific deviations from a global intercept that are effectively unit specific errors (total error is $a_i + \varepsilon_{it}$) that capture unit level time-invariant heterogeneity that has not been otherwise accounted for (Firebaugh et al., 2013; Bell & Jones, 2015). However, random effects assume that the independent variables are uncorrelated with the unit level effects terms (Firebaugh et al., 2013; Bell & Jones, 2015). In situations in which this assumption does not hold random effects estimates will be biased (Firebaugh et al., 2013; Bell & Jones, 2015). This can be regarded as a form of omitted variable bias (Firebaugh et al., 2013; Bell & Jones, 2015). To solve the endogeneity issues associated with the presence of unmeasured time-invariant heterogeneity, fixed effects strip out all of the 'between effects' in the data (often from time-invariant variables) by allowing the unit level terms to capture all unmodeled heterogeneity found in every observation in a unit (Philips, 2022a; Firebaugh et al., 2013; Bell & Jones, 2015). This can be accomplished by inserting dummy variables to represent these effects or, equivalently, by demeaning each variable (Bell & Jones, 2015; Mummolo & Peterson, 2018; Brüdel & Ludwig, 2015; Finkel, 2020). Fixed effects are specified by the equation:

$Yit = ß1X_{it} + ß1W_{it} + ß1Z_{it} + ß1M_{it} \ldots + \alpha i + \varepsilon_{it}$

Within this equation (Broniecki, 2018; Mummolo & Peterson, 2018):

- Y represents the dependent variable (CO_2 emissions),
- X_{it} represents independent variables Gini coefficient or income share,
- W_{it} represents the independent variable GDP,
- Z_{it} represents the independent variable population,
- M_{it} represents the independent variable MQOG, and
- a_i represents entity specific intercepts that capture all unmodeled heterogeneity found in every observation in a unit (Philips, 2022a; Firebaugh et al., 2013; Bell & Jones, 2015).

To examine the impact of income inequality on CO_2 emissions, two fixed effects models are estimated. The first model measures income inequality through the provincial level Gini coefficient while the second one uses the share of income received by the top 10% of income earners in each province, similar to Jorgenson et al. (2017). Additionally, each variable is log transformed in order to normalize the distribution of residuals and to make the results comparable to previous studies which frequently employ log transformations.

In order to deal with serial correlation, one lag of the dependent variable is included in the model (Armstrong, n.d; Fortin-Rittberger, 2015). Including a lag of the dependent variable makes the model a dynamic panel data model and, perhaps more importantly, helps to capture the effects of state-dependence in which the current value of a variable is related to its past values (Brüdel & Ludwig, 2015; Baum, 2020). To capture these affects, a dynamic model with a lagged dependent variable (LDV) is often required (Baum, 2020). Other studies that have examined the relationship between income inequality and CO_2 emissions have used various dynamic models in their studies (Hao, 2016; Baek & Gweisah, 2013; Huang & Duan, 2020). Within this study the dynamic model would be expressed as:

$$Yit = ß1Yi_{t-1} + \ ß1Xit \ \ldots + \alpha i + \varepsilon_{it}$$

Yi_{t-1} - the LDV

However, including an LDV within an FE framework can cause an issue that has become known as the Nickell bias (Leszczensky & Wolbring, 2022; Baum, 2020; Troeger, 2020; Philips & Pickup, 2022a). That is, in situations of small T the impacts of events close in time to the first observation may not have entirely worn off before the last observation (Philips & Pickup, 2022a). The effects of these events often resemble fixed differences between observations (the fixed effects) which makes it challenging for the model to separate out the fixed effects from the autoregressive type of data (Philips & Pickup, 2022a). In situations in which the real autoregressive parameter (the coefficient on the LDV) this bias is negative (Philips & Pickup, 2022a). One commonly used method to deal with the Nickell bias is the generalized method of moments (GMM) technique (Troeger, 2020). However, invalid moment conditions and problematic instruments can cause the can cause GMM estimators to produce biased estimates (Philips & Pickup, 2022b).

A method that avoids the issues associated with the GMM estimator is the orthogonal reparameterization approach (OPM) (Pickup et al., 2017; Pickup & Hopkins, 2022; Troeger, 2020). In essence, the OPM approach re-parameterizes the incidental parameters (the fixed effects) so that they are informationally orthogonal to the common parameters (the other parameters) (Pickup et al., 2017; Pickup & Hopkins, 2022. In a formal sense, this means that the slope of the log likelihood function in regards to the fixed effects is independent of the slope of the log likelihood function in regards to the common parameters (Pickup et al., 2017; Pickup &

Hopkins, 2022). Once the fixed effects have been transformed, priors can be placed on the parameters and the fixed effects can be integrated out which leaves a marginal posterior for the rest of the parameters (Pickup et al., 2017; Pickup & Hopkins, 2022). From here, Monte Carlo methods are used to sample values from the marginal posterior in order to find estimates for the common parameters (Pickup et al., 2017; Pickup & Hopkins, 2022). Three recent studies have used the OPM approach to check the validity of the results they obtained with dynamic models (Hopkins, 2020; Kriesi et al., 2020; Lerner, 2021). In a similar fashion to these previous studies the OPM method is used to confirm (or refute) the general trend of the parameter estimates of each variable. To the best of our knowledge, this is the first paper on this topic that has used the OPM as either a main method or mechanism to check the reliability of results.

The use of dynamic models also allows for both the short-run and long-run effects of each variable to be calculated. In the dynamic models used within this study, long-run effects are given by the formula: $M_x = (\beta_x)/(1 - \varphi)$ in which β is the short-run effect (coefficient) on an independent variable and φ is the coefficient on the lagged dependent variable (Philips, 2022b). Statistical analyses were performed using R the packages plm (Croissant & Millo, 2008; Croissant et al., 2022), OrthoPanels (Pickup et al., 2017), Stats (aov function) (Chambers et al., 1992), and lsr (Navarro, 2019). Long-run effects were calculated using the Stata commands ‘xtreg’ (StataCorp, 2021; StataCorp, n.d.A.) and ‘nlcom’ (StataCorp, 2021; StataCorp, n.d.B.). The Stata and R code used in the statistical analysis can be found in Appendix C.

5. Results and discussion

5.1. Descriptive statistics for each province

Each variable has slightly different overall trends which lends credence to the view that the measures may have different relationships with emissions over time. This can be seen in Figures 1 and 2 (see Appendix A for additional Figures 3 and 4). In most provinces, the Gini coefficient has either been relatively stable or has decreased to below its 1997 level over time. Conversely, in many provinces the income share has either remained reasonably stable or has increased over time to above its 1997 level, although in recent years some provinces have seen a downward trend. When analyzed through the Gini coefficient, Newfoundland and Labrador had the highest levels of income inequality from 1997 to 2019 while based on the income share metric, Alberta had the largest amount of income inequality (Table 4). The fact that the two income share measures yielded different provinces with the highest levels of inequality between 1997 to 2019 can potentially be attributed to the influence of changes in the different parts of the income distribution on the measures (De Maio, 2007; Hailemariam et al., 2019), but fully investigating this phenomenon is beyond the scope of this paper. When viewed using Figure 1, it is less clear which province had the lowest levels of income inequality from 1997 to 2019, although Alberta had the lowest average and median Gini coefficient during this period. Conversely, when viewed using Figure 2, Prince Edward Island had the lowest levels of income inequality from 1997 to 2019. Furthermore, Prince Edward Island had the lowest average and median share of income received by the top 10% of income earners (Table 4).

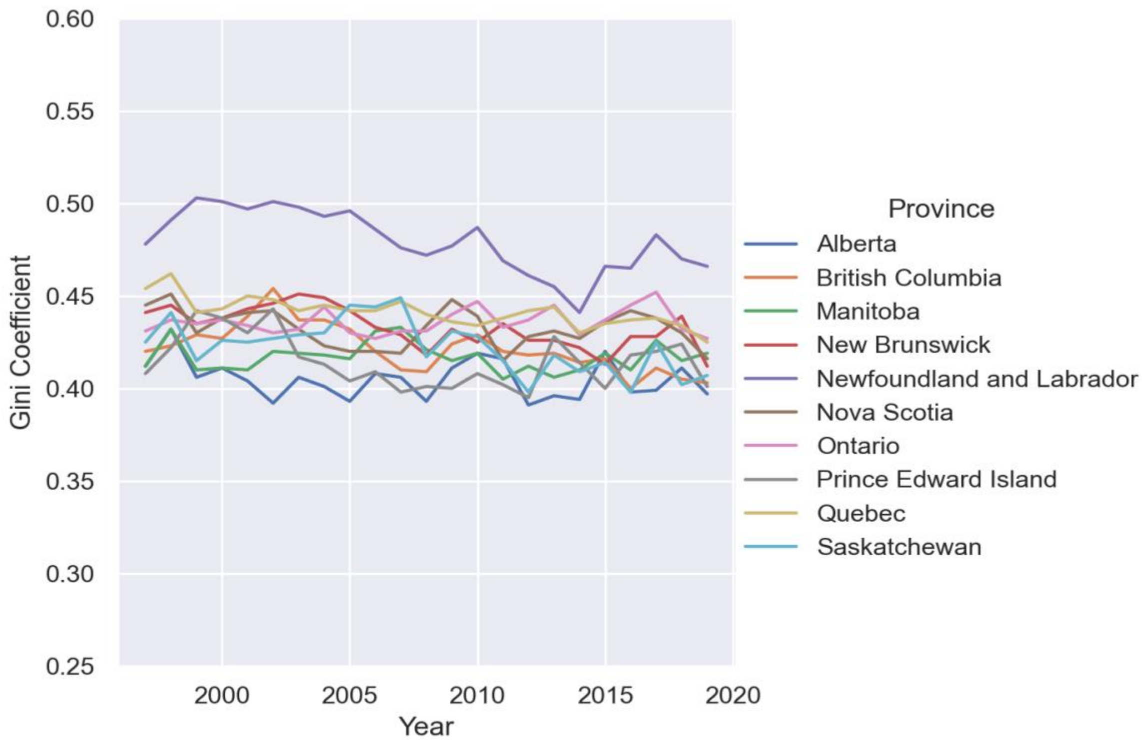

Figure 2. Gini coefficient by province over time

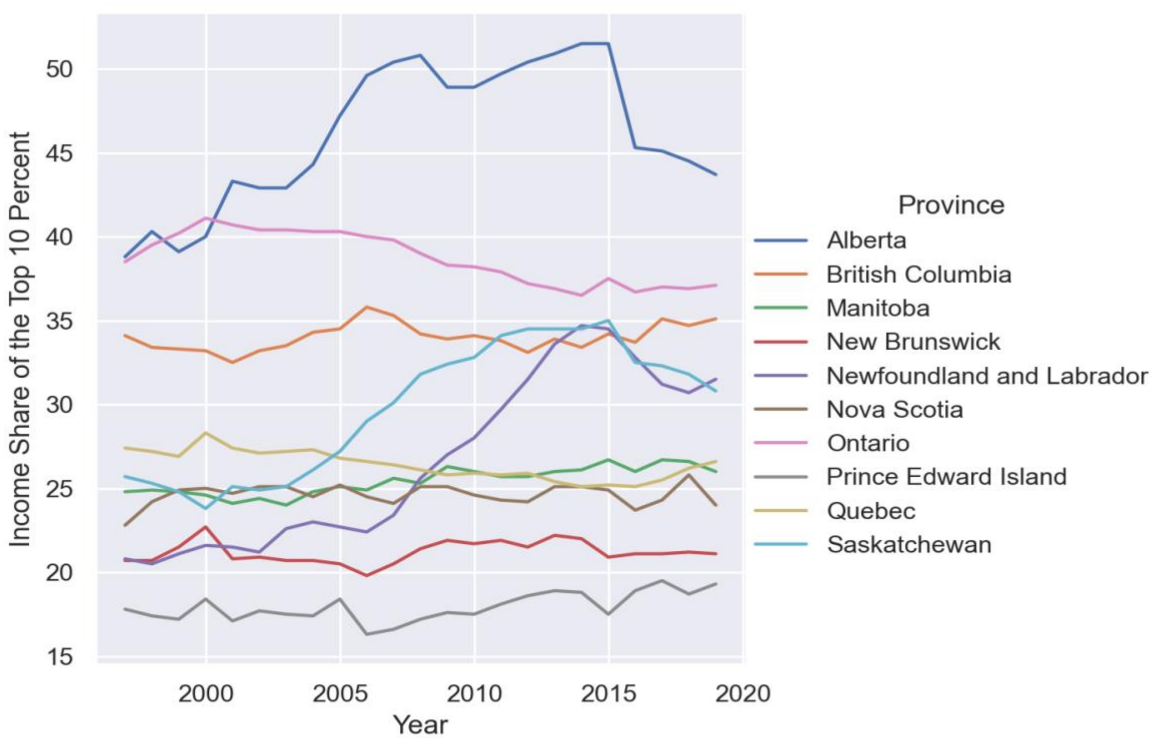

Figure 3. Income share of the top 10 % by province over time

A one-way ANOVA test reveals provinces to have a statistically significant effect on the Gini coefficient and income share over the time period 1997 to 2019. The p-value for the test involving the Gini coefficient was <2e-16 and the F-value was 71 while p-value for the test involving income share was also <2e-16 and the F-value was 250.8. In 2016 the provinces in which natural resources contributed the most to its GDP were Alberta, Saskatchewan, and Newfoundland, each of which has a well-developed energy sector (Alexander et al., 2018). Conversely, the least resource dependent regions in Canada were PEI, Ontario, and Nova Scotia (Alexander et al., 2018). Previous research has revealed oil abundance to be associated with lower levels of income inequality (Scognamillo et al., 2016; Kim et al., 2020, Berisha et al., 2021). When ranked using the income share, the three most resource dependent provincial economies in Canada all rank inside the top five (half) in terms of the provinces with the highest average levels of income inequality from 1997 to 2019. Similarly, both Alberta and Saskatchewan rank in the top half of Canadian provinces with the highest average levels of inequality from 1997 to 2019 when ranked using the Gini coefficient. Additionally, when the top three most resource dependent economies are compared to the bottom three most resource dependent economies using the results of the pairwise *t*-test for the Gini coefficient, six out of 9 comparisons show a statistically significant difference (see Tables 6 and 7 in Appendix B for pairwise t-test results). That comparison becomes even higher when using the income share in which 8 out of 9 comparisons show a statistically difference. These results are in contrast to previous research that showed oil abundance to be associated with lower levels of inequality (Scognamillo et al., 2016; Kim et al., 2020; Berisha et al., 2021). However, these results should be taken with some degree of caution given the fact that pair-wise *t*-tests yielded a high rate of statistically significant results which could be evidence of time-dependency. Future research could investigate the extent to which provincial economic reliance upon extractive industries is associated with higher levels of inequality using more robust statistical methods.

Table 4. Descriptive statistics for studied variables in each province from 1997 to 2019

Variable	Mean	Median	Standard deviation	Min	Max
Alberta					
CO_2 emissions ($MtCO_2$/yr)	193	194	24	154	225
Gini coefficient	0.405	0.406	0.011	0.391	0.432
Income share of the top 10%	46	45	4	39	52
British Columbia					
CO_2 emissions ($MtCO_2$/yr)	49	49	2	46	53
Gini coefficient	0.422	0.42	0.013	0.4	0.454
Income share of the top 10%	34	34	0.804	33	36
Manitoba					
CO_2 emissions ($MtCO_2$/yr)	13	13	0.655	12	14
Gini coefficient	0.417	0.416	0.008	0.405	0.433
Income share of the top 10%	25	26	0.818	24	27
Quebec					
CO_2 emissions ($MtCO_2$/yr)	64	64	3	60	70
Gini coefficient	0.441	0.442	0.008	0.425	0.462
Income share of the top 10%	26	26	0.870	25	28
Newfoundland and Labrador					
CO_2 emissions ($MtCO_2$/yr)	9.331	9.319	0.700	8.080	10.750
Gini coefficient	0.480	0.478	0.017	0.441	0.503
Income share of the top 10%	27	27	5	21	35
Nova Scotia					
CO_2 emissions ($MtCO_2$/yr)	18	18	2	14	22
Gini coefficient	0.432	0.432	0.010	0.415	0.451

Variable	Mean	Median	Standard deviation	Min	Max
Income share of the top 10%	25	25	0.633	23	26
New Brunswick					
CO_2 emissions ($MtCO_2$/yr)	16	17	3	11	21
Gini coefficient	0.433	0.433	0.011	0.412	0.451
Income share of the top 10%	21	21	0.662	20	23
Prince Edward Island					
CO_2 emissions ($MtCO_2$/yr)	1.3	1.3	0.127	1	2
Gini coefficient	0.415	0.413	0.014	0.395	0.443
Income share of the top 10%	18	18	0.852	16	20
Ontario					
CO_2 emissions ($MtCO_2$’/yr)	157	160	17	133	183
Gini coefficient	0.436	0.434	0.007	0.427	0.452
Income share of the top 10%	39	39	1	37	41
Saskatchewan					
CO_2 emissions ($MtCO_2$)	43	43	5	37	450
Gini coefficient	0.423	0.425	0.014	0.398	0.449
Income share of the top 10%	30	31	4	24	35

5.2. Associations between income inequality and CO_2 emissions

Table 5 shows that in both the dynamic fixed effects models population and the combined share of the mining, quarrying, and oil and gas sectors exhibited statistically significant positive short and long-run associations with CO_2 emissions while GDP was associated with statistically significant negative short- and long-run effects on CO_2 emissions. Although some previous studies found positive relationships between GDP (by itself) and CO_2 emissions (Jorgenson, 2017; Knight et al., 2017; Hailemariam et al., 2020), others *have* found evidence of an EKC –

which predicts higher levels of affluence to be associated with decreases in emissions – when GDP is measured through a quadratic term (Grunewald et al., 2017; Huang & Duan, 2020; Hailemariam et al., 2020; Uddin et al., 2020; Demir et al., 2019). When compared to studies that report both short and long-run effects, the findings of a negative short run association between GDP and CO_2 emissions resemble those of Demir et al. (2019) and Baek & Gweisah (2013) who found per capita income to have a negative effect on CO_2 emissions. In contrast, the detection of the negative long-run association of GDP with CO_2 emissions mirrors the findings of Baek & Gweisah (2013) but contrast with those of Demir et al. (2019). The findings on population and MQOG's positive associations are consistent with Jorgenson et al. (2017) who found population size and state fossil fuel production to be positively associated with to CO_2 emissions. In contrast, Hailemariam et al. (2019) found population size to be positively and negatively associated with CO_2 emissions over the long-run depending on the model that they employed.

Table 5. Results of four models: Describing the associations between income inequality using Gini coefficient and income share measure

Fixed Effects Models								
	Model 1: Gini coefficient				Model 2: Income share			
Variable	Parameter estimate	Stnd. parameter estimate	Std. error	t/z value	Parameter estimate	Stnd. parameter estimate	Std. error	t/z value
log(Gini)	-0.343	-6.55e-03	0.142	-2.409*				
log(Income Share)					0.142	8.24e-03	0.052	2.74**
lag(logCO_2)	0.865	0.06	0.035	25***	0.838	0.06	0.037	22.6***
log(GDP)	-0.143	-0.02	0.048	-3.01**	-0.184	-0.02	0.054	-3.4***
log(Pop)	0.325	0.01	0.112	2.9**	0.414	0.02	0.122	3.4***
log(MQOG)	0.027	7.63e-03	0.00	2.9**	0.021	5.76e-03	0.009	2.199*
log(Gini) - LR	-2.542	n/a	1.149	-2.21*				

log(Income Share) - LR					0.876	n/a	0.301	2.90**
log(GDP) - LR	-1.061	n/a	0.398	-2.67*	-1.133	n/a	0.340	-3.3***
log(Pop) – LR	2.414	n/a	0.876	2.76**	2.546	n/a	0.741	3.4***
log(MQOG) - LR	0.201	n/a	0.071	2.82**	0.126	n/a	0.058	2.19*
R^2	0.821				0.823			
Adjusted R^2	0.809				0.811			

OPM Models		
	Model 3: Gini Coefficient	Model 4: Income share
Variable	Parameter estimate (Credibility interval)	Parameter estimate (Credibility interval)
log(Gini)	-0.291 (-0.563, -0.008)	
log(Income Share)		0.089 (-0.016, 0.195)
lag(log(CO_2)	0.952 (0.871, 0.993)	0.934 (0.844, 0.992)
log(GDP)	-0.119 (-0.212,-0.025)	-0.136 (-0.245, -0.028)
log(Pop)	0.248 (0.026, 0.469)	0.291 (0.043, 0.536)
log(MQOG)	0.020 (0.001, 0.038)	0.015 (-0.004, 0.034)
log(Gini) - LR	-5.712 (-45.844, -0.196)	
log(Income Share) - LR		1.293 (-0.465, 9.162)
log(GDP) - LR	-2.385 (-17.491, -0.475)	-1.984 (-14.373, -0.471)
log(Pop) – LR	4.864 (0.614, 34.611)	4.253 (0.909, 28.836)
log(MQOG) - LR	0.385 (0.024, 2.643)	0.213 (-0.105, 1.784)

* denotes *p*-value of $p<0.05$;
**denotes *p*-value of $p<0.01$;
***denotes *p*-value of $p<0.001$.

Meanwhile, within the dynamic fixed effects models the Gini coefficient in each province exhibited a statistically significant negative short and long-run association with CO_2 emissions while the share of income received by the top 10% of income earners showed a statistically significant positive short and long-run association with emissions. These results mirror the results obtained by Hailemariam et al. (2019) who found the Gini coefficient to have a negative association with CO_2 emissions and income share to have a positive relationship over the long-run. This study's findings of positive long and short run associations between income share and CO_2 emissions within the dynamic fixed model also resemble the results of Jorgenson et al. (2017) who found income share to be associated with higher levels of CO_2 emissions. When compared to studies that report short and long-run effects, this study's findings concerning the negative short-run association of the Gini coefficient with CO_2 emissions are in contrast to Demir et al. (2019) and Baek & Gweisah (2013) who found the Gini coefficient to have positive short-run effects on CO_2 emissions. Conversely, the negative long run association of the Gini coefficient wiith CO_2 emissions resemble those of Demir et al. (2019) but contrast with those of Baek & Gweisah (2013). The findings of the positive short and long run associations of income share with CO_2 emissions resemble the short-run findings of C. Liu et al. (2019) but contrast with their long-run findings. Finally, the adjusted R squared of approximately 0.81 in each of the dynamic fixed effects model indicates that they are a good but not exceptional fit.

Broadly speaking, differences between the results of this study and previous studies can potentially be attributed to different time periods under consideration, the use of country-level versus subnational data, the different estimators employed in the various studies, and the use of different variables in each study. For example, Baek & Gweisah (2013) used yearly data from the United States from 1967 to 2008 while Demir et al. (2019) employed data concerning Turkey from 1963 to 2011. Uddin et al. (2020) has demonstrated that the relationship between income inequality measured through the Gini coefficient and emissions can vary over time which suggests that the use of longer time periods could lead to different results. However, C. Liu et al. (2019) employed data across American states and the District of Columbia from 1997 to 2015 which is closer to the time period employed during this study. Differences between the two studies in terms of the long-run associations of income share with CO_2 emissions may be explained by C. Liu et al.'s (2019) use of the variable "…ratio of manufacturing output to GDP" (C. Liu et al., 2019, p.383) instead of the MQOG sector's contribution to GDP. Furthermore, C. Liu et al. (2019) do not use the variable population and include the additional variable per capita energy consumption.

Results of the orthogonal reparameterization models used to check the reliability of the results obtained through the dynamic FE models are reported in Table 3 and are expressed in Bayesian equal tailed credibility intervals (Pickup et al., 2017), with the top number representing the median value and bottom two numbers representing either side of the 95% credibility interval. Expressing the results through Bayesian credibility intervals also incorporates Imbens' (2021) recommendations that researchers report results where appropriate using Bayesian posterior intervals to overcome problems associated with the use of p-values. The robustness check through the OPM estimator largely confirms the majority of the results of the dynamic fixed effects models for both short and long-run associations, with the possible exceptions of the variables income share and MQOG in model 4. The fact that the credibility interval of both these variables contains zero for both their short and long-run associations implies that the findings on these variables should be taken with some degree of caution and that the results surrounding the income share variable should probably be regarded as inconclusive. However, the fact that three of the four models found reliably positive short and long run associations for the MQOG variable could mean that the estimates for this variable can be taken as more definitive than those surrounding the income share variable.

Given the emissions intensities of the MQOG sectors – in particular the oil and gas sectors – it is should be unsurprising that having larger shares of these industries is mostly associated with increases in CO_2 emissions in both the short and the long run. Additionally, the fact that GDP exhibited a negative association with CO_2 emissions in both the short and long run can be understood as evidence that at least some provinces having managed to decouple economic growth from CO_2 emissions. Furthermore, it suggests that Canada has surpassed the area of GDP at which the EKC is likely to present itself, as seen with America in Baek & Gweisah (2013). This would imply that CO_2 emissions can be expected to decrease as GDP rises (Baek & Gweisah, 2013). However, the positive association between population and CO_2 emissions over both the short and long run can be interpreted as meaning that increased demand for energy intensive services during the time period under consideration outstripped any efficiency gains that were made during the years that have been studied. If population gains continue to outstrip adoption of innovations in energy efficiency and fuel switching, this could have implications for the levels that carbon pricing may need to be set at (Kruse-Andersen, 2020).

When viewed in light of the potential underlying mechanisms that could drive an association between income inequality and CO_2 emissions, the results would seem to confirm the validity of the 'marginal propensity to emit' hypothesis while giving neither cause to reject or accept the 'consumption competition hypothesis.' Indeed, the fact that the Gini coefficient had s statistically significant negative associations with CO_2 emissions as predicted by the 'marginal propensity to emit hypothesis' suggests that this framework may be accepted as a valid explanation for the relationship between income inequality and CO_2 emissions within this study. However, the fact that the dynamic fixed effects model showed income share to be associated with higher levels of CO_2 emissions while the OPM estimator showed there to be no association between the two variables means that the ‘consumption competition’ hypothesis should not be accepted or rejected (results are inconclusive). Within the dynamic fixed effects model it is possible that the findings of a positive relationship between income share and CO_2 emissions has been partially driven by emissions from the housing sector since increases in income inequality may increase the number of people living in houses of poor thermal performance and may impact people’s ability to purchase energy saving technology (Galvin & Sunikka-Blank, 2018). Future research could further investigate the linkage between CO_2 emissions from the housing sector and income inequality.

It should also be noted that the observed historical association between CO_2 emissions and income inequality cannot be separated from the fossil fuel intensive nature of economic activity (Hausfather, 2021). Consequently, as climate policies begin to become more stringent in the years ahead (Environment and Climate Change Canada, 2022), the association between income inequality and CO_2 emissions should begin to diminish in strength.

6. Conclusions

Through descriptive statistics and data visualisations of income share and the Gini coefficient, this study has shown Alberta and Newfoundland to have the highest levels of income inequality in Canada, respectively, from 1997 to 2019. Throughout this same period, average and median income share was lowest in P.E.I., a trend that is confirmed by the geo-spatial visuals and the line graphs shown in figures 2 and 3. Subsequent analysis through a one-way ANOVA-test revealed provinces to have a statistically significant effect on both measures of income inequality. Moreover, pairwise t-tests and rankings of provinces according to average income share and the Gini coefficient suggest that levels of income inequality may be higher in provinces whose economies are most reliant upon the oil and gas sectors. An interesting topic for future research could be whether the inequality in Newfoundland is associated with the expansion of the MQOG sector in Alberta, as many Newfoundland residents have travelled to places in Alberta to work on oil and gas related projects (Antie, 2020, CBC News, 2007).

Additionally, the fact that inferential statistics showed the Gini coefficient to have statistically significant short and long-run associations with emissions suggests the 'marginal propensity to emit' hypotheses can be accepted as a valid depiction of the relationship between income inequality and CO_2 emissions in Canada. However, the fact that income share only exhibited statistically significant short and long-run associations with CO_2 emissions within the dynamic fixed effects model implies that the 'consumption competition' hypothesis should be tested again in future research using different methods since the results achieved in this study are inconclusive for this variable.

There are a number of limitations present in this study related to data availability and the four employed models (see equations 1 and 2). Firstly, due to data unavailability, the study did not include measures of population density, urbanization, and annual imports which could have helped to control for the impact of carbon leakage. Secondly, this study's reliance on aggregated data could conceal the effect of location on CO_2 emissions. A more detailed discussion of the impact of scale is contained in the literature review. Future studies could address this gap by examining situations in which location and income inequality may interact to impact CO_2 emissions within an area. Thirdly, this study contains limitations that stem from the data sources used to acquire data on income share and CO_2 emissions. In regards to the data on income share, the measurement of income through the LAD can obscure the effects of income earned by residents of a province outside of that jurisdiction on income inequality. Moreover, Canada's GHG inventory excludes scope 3 emissions, limiting the ability of this study to detect the full effect of individual consumption decisions on CO_2 emissions. Additionally, fixed effects models strip out all between variation from the coefficient estimates which may contain important information, lowering the amount of variation captured in the model (Bell & Jones, 2015; Mummolo & Peterson, 2018). Future studies could potentially address these limitations by conducting research on economic inequality and CO_2 emissions at the sub-national level using the random-effects-between-within model described by Bell & Jones (2015). Furthermore, this study conducts ex-post analysis to assess the historical relationship between income inequality and CO_2 emissions. With new unfolding climate policy in Canada, ex-ante analyses are equally important to make projections about the impact of these policies on future CO_2 emissions. Relatedly, relatively new provincial climate policies were excluded as variables in this study which could lead to some form of omitted variable bias since these policies may have impacted CO_2 emissions in certain provinces during the last few years of emissions reporting. Our findings, however, could be used as exogenous inputs into energy-economy models to inform ex-ante studies to help policymakers prepare for the impacts of climate policy on income inequality and vice versa. The results of this study could also be used to validate endogenously defined parameters around the income distribution within energy-economy models. Additionally, to remain consistent with much of the past literature, this study has only assessed the impact of income inequality on CO_2 emissions, as opposed to CO_2 equivalent emissions. Future studies could address this gap by using other GHGs or CO_2 equivalent emissions as a dependent variable.

Despite these limitations, the study provides important insights for academic research and public policy-making. First, the results help to advance the academic understanding of the relationship between income inequality and CO_2 emissions. Taken together these results suggest that in Canada the Gini coefficient is negatively associated with CO_2 emissions while no definitive conclusions can be drawn about the impact of income share of the top 10% on CO_2 emissions. Moreover, these findings demonstrate that the 'marginal propensity to emit' can be a valid conceptual understanding of the relationship between income inequality and CO_2 emissions.

Conservatively, from a policy-making perspective, this study may indicate that any potential reductions in CO_2 emissions achieved by redistributive economic policies that lower income inequality through the income share channel could be offset by rises in CO_2 emissions caused by the Gini coefficient channel, assuming that changes in the Gini coefficient and the income share happen concurrently. If there is indeed no statistically significant association of income share with CO_2 emissions, then reductions in income inequality may result in higher levels of emissions than there would have been without the lowering of income inequality. However, the results of this study should not be taken to imply that future changes in income inequality may automatically produce higher or lower levels of emissions as this is something that will also be determined by the design and stringency of a jurisdiction's climate policy. Furthermore, as stated previously, any associations between income inequality and CO_2 emissions should be expected to decrease as climate policy begins to reduce CO_2 emissions and accelerate the decarbonization of the Canadian economy (Hausfather, 2021; Environment and Climate Change Canada, 2022b). Finally, these results also underscore the importance of regionally targeted policies that consider the interconnections between measures designed to reduce emissions and other policy objectives.

This findings of a negative association between income inequality and CO_2. emissions could indicate the need to balance potentially competing values that citizens believe government policy should embody such as efficiency, the polluter pays principle, and the ability to pay principle (Dietz & Atkinson, 2010). Based on the results of this paper, decreasing income inequality may imply that an increasing share of CO_2 emissions can be associated with the consumption of lower income earners, a phenomenon that could hold implications for the 'polluter pays' principle in a situation in which policies designed to reduce CO_2 emissions are imposing economic costs on society (Dietz & Atkinson, 2010). However, at times, this may be in tension with the ability to pay principle, an objective that people also believe to be important (Dietz & Atkinson, 2010). Policy-makers can help to minimize the number of potential scenarios in which the ability to pay principle, the polluter pays principle, and policy efficiency may be tension with one another by selecting the right combination of policy instruments to reduce CO_2 emissions in Canada (Dietz & Atkinson, 2010). In situations where policy design is unable to remove any potential tensions between these values, the balance struck between them will ultimately be a social and political trade-off choice that elected officials may need to make.

Future research could use ex-ante modelling to project the impact of lower or higher levels of economic inequality on emissions and vice versa, or focus on determining the extent to which income inequality is linked to higher CO_2 emissions from the housing sector. Additionally, future research could use disaggregated data from the municipal level within Canadian provinces to shed light on whether any regional level complexities in the relationship between income inequality and CO_2 emissions exist. Another fruitful area for future research could be examining the impact that different climate policy scenarios may have on inequality through ex-ante modelling.

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Appendix A. Additional figures

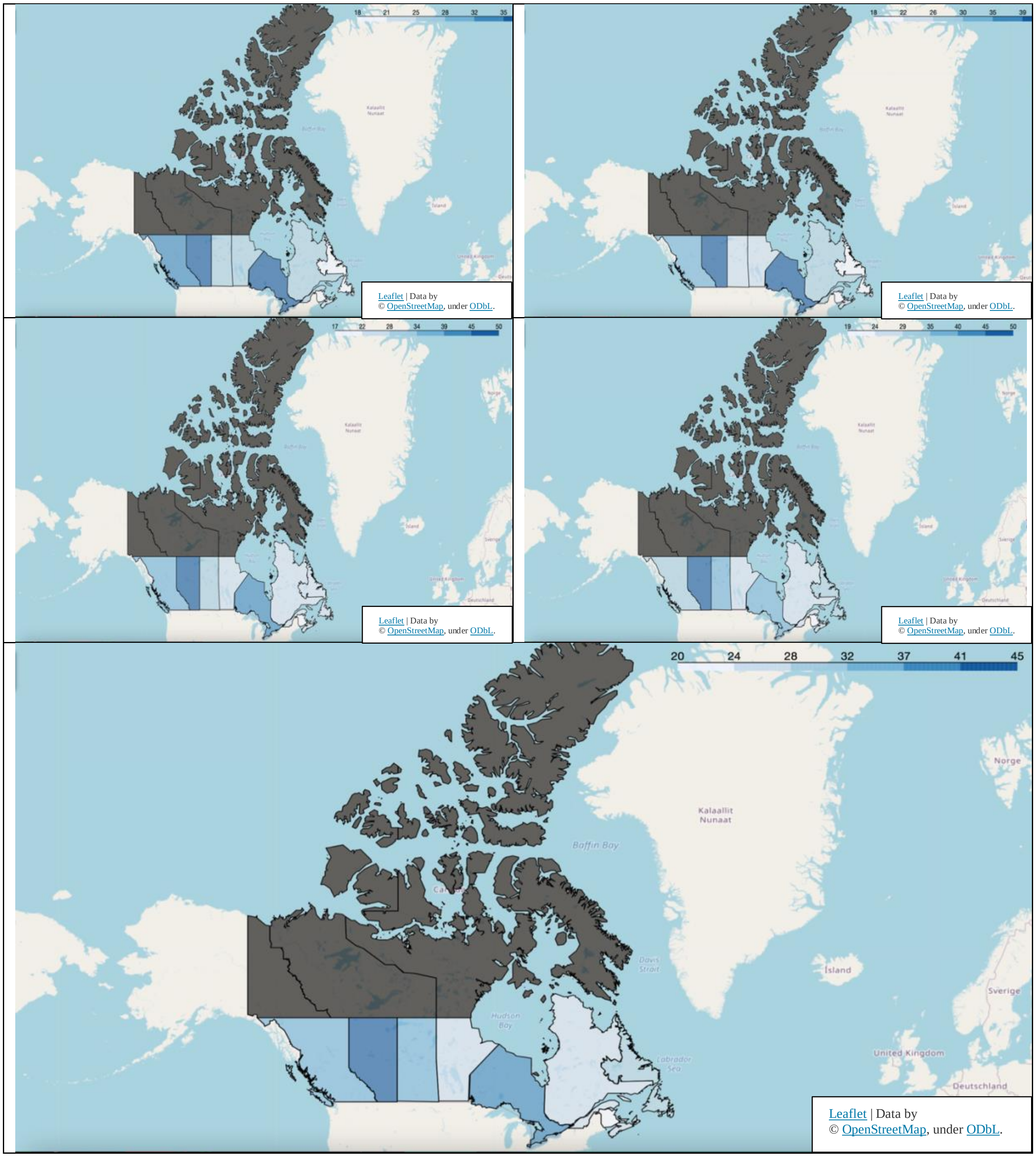

Figure 4. Spatial distribution of income inequality across Canadian provinces over five-year intervals measured through the income share metric (1999-2019). Darker colours denote higher levels of inequality.

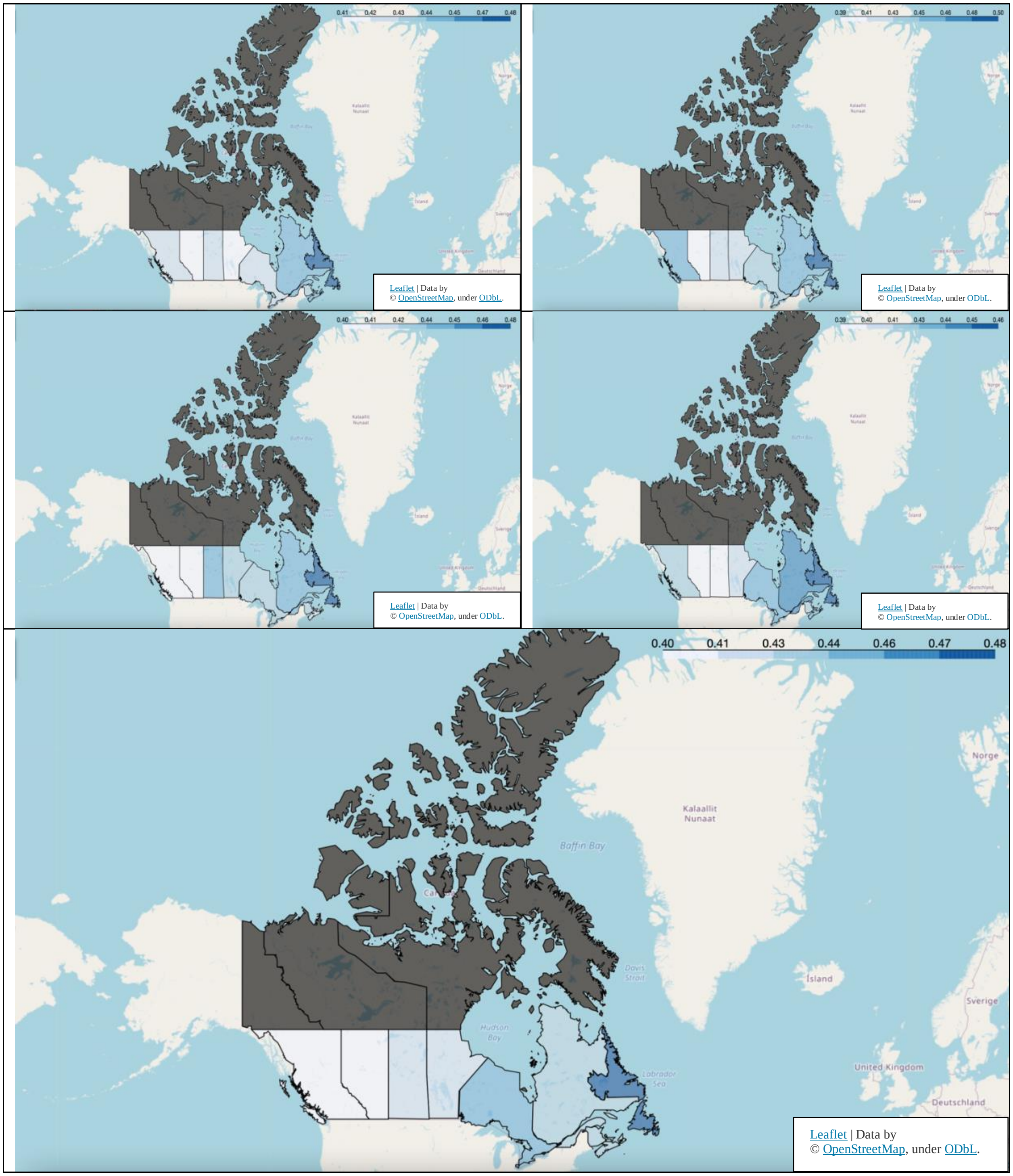

Figure 5. Spatial distribution of income inequality across Canadian provinces over five-year intervals measured through the gini coefficient (1997-2017). Darker colours denote higher levels of inequality.

Appendix B. Additional tables

Table 6. Pairwise comparisons using t tests with pooled SD for Gini coefficient

data: Gini and Province					
	Alberta	British Columbia	Manitoba	New Brunswick	Newfoundland
British Columbia	7.0e-05	-	-	-	-
Manitoba	0.0124	1.0000	-	-	-
New Brunswick	1.5e-12	0.0206	0.00014	-	-
Newfoundland and Labrador	< 2e-16	< 2e-16	< 2e-16	< 2e-16	-
Nova Scotia	3.6e-12	0.0307	0.00024	1.0000	< 2e-16
Ontario	6.6e-15	0.0011	3.4e-06	1.0000	< 2e-16
Prince Edward Island	0.0811	0.3918	1.000	7.0e-06	< 2e-16
Quebec	< 2e-16	1.0e-06	6.6e-10	0.1731	< 2e-16
Saskatchewan	2.0e-05	1.000	0.8418	0.0450	< 2e-16
	Nova Scotia	Ontario	Prince Edward Island	Quebec	
British Columbia	-	-	-	-	
Manitoba	-	-	-	-	
New Brunswick	-	-	-	-	
Newfoundland and Labrador	-	-	-	-	
Nova Scotia	-	-	-	-	
Ontario	1.0000	-	-	-	
Prince Edward Island	1.3e-05	1.1e-07	-	-	
Quebec	0.129	0.842	1.1e-11	-	
Saskatchewan	0.065	0.0030	0.220	3.9e-06	
***p*-value adjustment method: holm**					

Table 7. Pairwise comparisons using t tests with pooled SD for income share

data: Income Share and Province					
	Alberta	**British Columbia**	**Manitoba**	**New Brunswick**	**Newfoundland**
British Columbia	< 2e-16	-	-	-	-
Manitoba	< 2e-16	< 2e-16	-	-	-
New Brunswick	< 2e-16	< 2e-16	5.8e-07	-	-
Newfoundland and Labrador	< 2e-16	< 2e-16	0.510	2.0e-10	-
Nova Scotia	< 2e-16	< 2e-16	0.610	8.9e-05	0.571
Ontario	< 2e-16	3.1e-08	< 2e-16	< 2e-16	< 2e-16
Prince Edward Island	< 2e-16	< 2e-16	< 2e-16	0.00018	< 2e-16
Quebec	< 2e-16	< 2e-16	0.610	8.2e-10	0.800
Saskatchewan	< 2e-16	5.3e-07	4.6e-07	< 2e-16	0.00029
	Nova Scotia	Ontario	Prince Edward Island	Quebec	
British Columbia	-	-	-	-	
Manitoba	-	-	-	-	
New Brunswick	-	-	-	-	
Newfoundland and Labrador	-	-	-	-	
Nova Scotia	-	-	-	-	
Ontario	< 2e-16	-	-	-	
Prince Edward Island	4.41e-15	< 2e-16	-	-	
Quebec	0.095	< 2e-16	< 2e-16	-	
Saskatchewan	1.4e-09	< 2e-16	< 2e-16	0.00013	
***p*-value adjustment method: holm**					

Appendix C. Datasets and files containing STATA/R/Python code

https://github.com/nconrad95/CO2_IncEq_Can