



Carbon emissions, income inequality and economic development

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Abstract

This paper investigates whether changes in income inequality affect carbon dioxide (CO₂) emissions in OECD countries. We examine the relationship between economic growth and CO₂ emissions by considering the role of income inequality in carbon emissions function. To do so, we use a new source of data on top income inequality measured by the share of pretax income earned by the richest 10% of the population in OECD countries. We also use Gini coefficients, as the two measures capture different features of income distribution. Using recently innovated panel data estimation techniques, we find that an increase in top income inequality is positively associated with CO₂ emissions. Further, our findings reveal a nonlinear relationship between economic growth and CO₂ emissions, consistent with environmental Kuznets curve. We find that an increase in the Gini index of inequality is associated with a decrease in carbon emissions, consistent with the marginal propensity to emit approach. Our results are robust to various alternative specifications. Importantly, from a policy perspective, our findings suggest that policies designed to reduce top income inequality can reduce carbon emissions and improve environmental quality.

Keywords Carbon dioxide emissions · Income inequality · Economic development · Environmental Kuznets curve · Panel data

JEL Codes O4 · Q0 · Q1 · Q3

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1 Introduction

Does the distribution of income affect carbon dioxide emissions? Does this relationship depend on the level of economic development? Answers to these questions have important implications for economic and environmental policies, as the surge in income inequality and greenhouse gas emissions are among the most pressing problems of our time. According to the Intergovernmental Panel on Climate Change (IPCC), CO₂ emissions from fossil fuel combustion and industrial processes constitute the largest contribution to greenhouse gas emissions, accounting for 65% of the total in 2010. It also contributed about 78% of the increase in total greenhouse gas emissions for the period 1970–2010. The past decades have also witnessed a sharp increase in income inequality that may have significant implications for climate change. As a result, the relationship between income inequality, economic growth and carbon emissions has been a hotly debated topic in academia and policy circles in recent years (see, e.g., Baek and Gweisah 2013; Hao et al. 2016; Grunewald et al. 2017; Jorgenson et al. 2017; Hübler 2017 among the most recent contributions).

Despite the rapidly growing number of studies that have investigated the inequality–emissions nexus, the evidence provided by existing studies is inconclusive. One of the main reasons is the lack of reliable historical data on the evolution of income inequality (Berthe and Elie 2015). Consequently, most empirical studies on the relationship between income inequality and CO₂ emissions analyze the relationship between the two variables at a single point in time using short-span data that are characterized by discontinuity over time and lack of comparability across countries. As pointed out in Atkinson and Brandolini (2006), empirical results of existing studies on income inequality can be seriously affected by data discontinuity. This limitation in data availability in previous empirical work created the potential for measurement errors, as well as difficulty in controlling for unobserved common factors as the time dimension is not sufficiently long enough for modern panel data estimation techniques that require large N and large T . The issue of measurement errors and comparability of data across units remains a challenge in studying inequality–emissions nexus using cross-country data. Moreover, as income inequality is persistent and a slow-moving process, it requires long panel data with specifications accounting for the dynamics. Existing studies focus on the static relationship between the two variables using relatively short-span data. Since CO₂ emissions and income inequality are likely to have unobserved common causes, simple cross-sectional relationship between carbon emissions and income inequality may yield biased and inconsistent estimate of how changes in income inequality affect CO₂ emissions. Nevertheless, most previous studies rely on simple traditional econometric methods such as the OLS and fixed effects that do not account for endogeneity, heterogeneity and cross-sectional dependence. To the best of our knowledge, the studies that are closely related to our paper are Grunewald et al. (2017) which accounts for unobserved heterogeneity in intercepts within groups using group fixed effects estimator and Jorgenson et al. (2017) which uses the measure of top income inequality for the US states. Our paper compliments these studies by accounting for slope heterogeneity in each individual units and cross-sectional dependence in errors employing common correlated effects mean group estimator (CCEMG) using

six decades of panel data. We also address endogeneity issues that may arise from simultaneity, omission of relevant variables and measurement errors.

In this paper, we examine the nexus between income inequality and CO₂ emissions using a new source of data on economic inequality: the top income inequality measured by the share of personal income received by the richest 10% of the population in selected OECD countries. As argued in Jorgenson et al. (2017), this measure of economic inequality is in line with the political economy model of inequality and the Veblen effect—the emulative influence of the wealthy to consume expensive goods and services as a mode of status-seeking. To capture the variations in inequality that arises from the differences in lower- and middle-income households, we also use the Gini index measure of inequality. We use annual data of 65 years per country spanning the period 1945–2010. Our study is the first to use such long cross-country historical data on top income inequality that allows us to study the long-run effect of top income inequality on the environment via CO₂ emissions. We aim to fill the gap in the literature that arises from paucity of reliable historical data on economic inequality which in turn has significant bearings on econometric misspecifications.

The main novelties of our study are threefold. First, we use a unique and improved panel data set that spans over more than half a century that minimizes measurement errors and fosters cross-country comparisons over long horizon. This is an important quality of data in examining long-run relationship among economic development, income inequality and carbon emissions where they are characterized by slow changes over time. We use income share of the top 10% as a measure of income inequality which is consistent with the analytical approaches proposed in the political economy hypothesis and the Veblen effects. Thus, unlike previous studies that use Gini coefficients of income inequality, our measure of top income inequality captures the potential economic and political powers and the emulative influence of the wealthy (see Jorgenson et al. 2017). To compare our results with the extant literature that uses Gini coefficients, we also use the Gini index measure of income inequality which is relevant to the marginal propensity to emit approach. Second, based on data properties and economic theories, our specification includes the lagged dependent variable to account for dynamics, persistence and the slow-moving nature of the indicators. Surprisingly, none of the existing studies account for these key features of data. Ignoring this important specification issue by the previous studies means that their econometric method is likely to be misspecified that may result in biased and inconsistent results. Third, we address potential endogeneity bias that may arise from simultaneous determination of income inequality and carbon emissions and omission of relevant time-variant variables by utilizing novel estimation techniques. In addition, we account for heterogeneity and cross-sectional dependence in our econometric specifications.

Our findings reveal that an increase in top income inequality is associated with an increase in carbon emissions. Further, our findings confirm that the effect of national income on emissions is conditional on the level of economic development. That is, national income plays a negative role on carbon emissions when the level of economic development is sufficiently high. This is consistent with the hypothesis that environmental quality is a superior good when income increases, and therefore, the wealthy prefer to protect the environment. The Gini index measure of inequality is

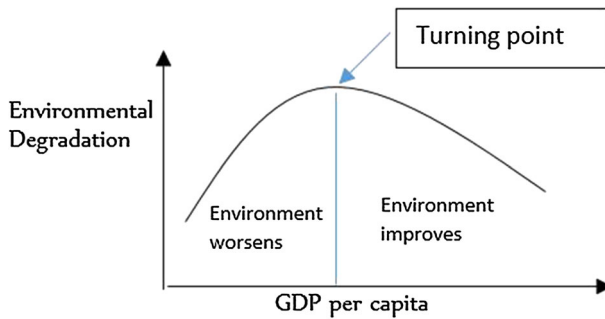


Fig. 1 Environmental Kuznets curve

negatively associated with carbon emissions in line with the marginal propensity to emit approach.

The remainder of the paper is organized as follows. In Sect. 2, we provide a brief review of the related literature. Section 3 presents the data and econometric methodology we employed in this paper. Section 4 presents our empirical results and discussions. Section 5 concludes.

2 Literature review

The relationship between income inequality and environmental degradation via greenhouse gas emissions has been featured in the recent literature (see, e.g., Qu and Zhang 2011; Golley and Meng 2012; Baek and Gweisah 2013; Guo 2014; Zhang and Zhao 2014; Hübler 2017; Grunewald et al. 2017; Wolde-Rufael and Idowu 2017). The foundation for the analysis on the role that income inequality plays on mediating the nexus between economic development and environmental degradation is the famous environment Kuznets curve (EKC) hypothesis. The EKC hypothesis suggests an inverted U-shaped relationship between economic development and environmental degradation, as depicted in Fig. 1. That is, environmental quality deteriorates as per capita income increases at the initial stage of development but improves after a certain threshold of per capita income.

Recent studies suggest that not only income, but also its distribution is an important factor that determines the level of aggregate carbon emissions and hence the quality of the environment (Hao et al. 2016; Jorgenson et al. 2017; Kashwan 2017; Knight et al. 2017; Kasuga and Takaya 2017). Therefore, there is a growing interest in analyzing the role of national per capita income along with its distribution on per capita carbon emissions and its implication for the global environment.

There are several transmission mechanisms through which income distribution could potentially affect per capita carbon dioxide emissions. Boyce (1994, 2007) proposes a political economy approach to explain theoretically the negative impact of income inequality on environmental quality. He argues that the wealthy class of society have a tendency for more environmental pollution as they own polluting firms and have higher carbon-intensive consumption of industrial goods and services. Under

Boyce's political economy model, the wealthy class have bargaining power to alter policy environments so as to avoid costlier environmental protection. Specifically, in a model of power-weighted social decision rule, he demonstrates that the wealthy class use their economic and political bargaining power to undermine policy makers' efforts on environmental protection. Using their economic and political power, the wealthy elites derive the pay-off from their polluting activity, while the poor class of society bear the costs of environmental pollution. In their empirical study, Boyce et al. (1999) show that the political economy model of income inequality and environmental quality predicts that more income inequality leads to a deterioration in environmental quality. Subsequent studies also suggest that promoting equality in income and political power is very important in reducing environmental degradation (Ciplet et al. 2015).

Scruggs (1998) challenges the hypothesis proposed by Boyce et al. (1999). Assuming that environment is a normal good, an increase in per capita income could be associated with the same level of preference for environmental degradation. If environment is a superior good, then an increase in income may be associated with a lower level of preference for environmental degradation. The reason is that, the wealthy prefer a clean environment and hence promote environmental regulations as income increases. This behavior is in line with environmental Kuznets curve hypothesis.

The other proposed hypothesis to explain that the nexus between income inequality and CO₂ emissions is the marginal propensity to emit (MPE). Based on the Keynesian concept of marginal propensity to consume (MPC), the MPC for low-income households is higher than the MPC for high-income households. This suggests that equality through an increase in the income of the poor to catch up the rich means a higher marginal propensity to consume energy, and hence a higher marginal propensity to emit. Therefore, an increase in equality in a society tends to harm environment, suggesting a mechanism that explains a negative relationship between income inequality and carbon emissions.

Empirically, a number of studies have examined the effect of national income and its distribution on per capita carbon emissions. However, the evidence from these studies is at best mixed depending on sample, time periods and econometric techniques (Hübler 2017; Grunewald et al. 2017; Kasuga and Takaya 2017). Since the pioneering work of Ravallion et al. (2000), the empirical literature provides conflicting results on the relationship between carbon emissions and income inequality (see, for example, Berthe and Elie 2015 for the survey of the literature). Several studies, such as Ravallion et al. (2000), Heerink et al. (2001), Borghesi (2006), Qu and Zhang (2011), Guo (2014) and Hübler (2017), show that income inequality is negatively associated with carbon emissions, which suggests the existence of a trade-off between promoting equality and improving environmental quality.

Using pooled OLS estimators and panel data for 42 countries for the period 1975–1992, Ravallion et al. (2000) find a negative relationship between income inequality and aggregate carbon emissions. This finding indicates that controlling climate change and promoting equity may require some trade-off between these two aims. Subsequent studies, such as Heerink et al. (2001), find that an increase in income inequality leads to a decrease in carbon dioxide emissions. Among recent contributions, Hübler (2017) uses quantile regressions and finds a negative relationship between income

inequality and carbon emissions while the results from his fixed effect estimations show insignificant relationships between the two variables.

The recent literature suggests that there is a positive relationship between inequality and emissions. For example, Golley and Meng (2012) investigate variations in carbon dioxide emissions across households using the 2005 China's Urban Household Income and Expenditure Survey. They find that richer households have the tendency for more emission per capita and find that there is an increasing marginal propensity to emit (MPE) over income. They conclude that increasing MPE implies a win–win case instead of trade-off. That is, social equity through redistribution of income from rich to poor households reduces carbon emissions and hence improves environmental quality. Boyce (1994), Magnani (2000) and Wilkinson and Pickett (2010) are also among the notable studies that provide a variety of explanations for the negative association between income inequality and environmental quality. Boyce (2007) and Wilkinson and Pickett (2010) argue that income inequality undermines social cohesion and trust, leading to reduced social responsibility to ensure the quality of the environment. In line with this, Vona and Patriarca (2011) argue that income inequality has a negative impact on the environment by preventing the development and diffusion of new environmental technologies. Baek and Gweisah (2013) examine the effect of income inequality on environment using time series data for the USA. Their findings show that an increase in income inequality is harmful to environment.

Grunewald et al. (2017) employ group fixed effects estimator to examine the role of income inequality on carbon emissions. They show that the relationship between the two variables depends on the level of income. Specifically, they find a negative association between income inequality and per capita carbon emissions in low- and middle-income economies and a positive association in upper middle-income and high-income economies. Using time series cross-sectional Prais–Winsten regression on US state level data for the period 1997–2012, Jorgenson et al. (2017) find a positive relationship between carbon emissions and the income share of the top 10%. They find that the Gini index has no significant effect on emissions. Hao et al. (2016) investigate the relationship between income inequality and carbon emissions in 23 Chinese provinces for the period 1995–2012. Their results show that inequality and emissions are positively associated. Borghesi (2006) examines the causal relationship between the Gini index of income inequality and carbon emissions using the OLS and fixed effect estimators in a sample of 37 countries for the period 1988–1995. His preferred fixed effect results show that there is no causal relationship between income inequality and carbon emissions, supporting the findings of Jorgenson et al. (2017). Table 1 summarizes the findings of some of the most recent empirical studies on the nexus between income inequality and carbon emissions.

To sum up, the existing literature provides mixed and inconclusive evidence on the relationship between income inequality and CO₂ emissions mainly due to the econometric model misspecifications and lack of comparable inequality data over time and space. None of these studies account for heterogeneity and cross-sectional dependence across countries except for Grunewald et al. (2017). Using group fixed effects estimator and data for 158 countries for 1980 to 2008, Grunewald et al. (2017) account for unobserved heterogeneity that are common within groups of individuals. In terms of data, Jorgenson et al. (2017) uses top income inequality for US states for

the period 1997–2012. Our paper compliments these studies by accounting for slope heterogeneity in each individual unit and cross-sectional dependence in errors, as well as addressing endogeneity that may arise due to simultaneity and omission of relevant variables. In addition, we use long panel data on top income inequality that allows us to estimate long-run relationships between the variables. This is important because inequality is a slow-moving process and needs long enough data series to capture the changes over time. In light of these shortcomings in existing studies, this paper attempts to fill the gap in the existing literature in terms of both estimation techniques and data.

There are a few studies that have investigated the relationship between inequality and other types of pollutants, such as sulfur dioxide (SO₂) and nitrogen oxide (NO_x) with mixed results. For example, Torras and Boyce (1998) show that an increase in Gini coefficients leads to an increase in SO₂ emissions in low-income countries and a decrease in SO₂ emissions in high-income countries. Brännlund and Ghalwash (2008) show that a decrease in income inequality through redistribution will result in an increase in emissions of SO₂ and NO_x. Heerink et al. (2001) and Clement and Meunie (2010) find that an increase in the Gini index has no effect on SO₂ emissions but causes an increase in water pollution. It is worth to note that the IPCC identifies CO₂ as the single largest pollutant that contributes about 65% of the total greenhouse emissions in 2014.

3 Data and methodology

3.1 Data

We use over half a century of panel data spanning over the period 1945–2010 for 17 OECD countries that include Australia, Canada, Denmark, Finland, France, Germany, Japan, Italy, Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, UK and USA. The dependent variable is log of per capita carbon emissions. Data for CO₂ emissions in metric tons of carbon are from Oak Ridge National Laboratory (ORNL) Information Analysis Centre. The ORNL data are the most comprehensive and comparable data source of national CO₂ emissions estimated from fossil fuels and cement manufacturing. Data on income inequality are obtained from World Wealth & Income Database and Madsen et al. (2018). Data on real GDP per capita and population are from Maddison Project database. As additional control variable, we use data on share of agricultural value added from Madsen and Ang (2016). The rationale for controlling for the share of agricultural value added is to account for transition in the structure of the economy in line with the environmental Kuznets curve hypothesis. That is, environmental degradation tends to increase in the transition from rural to urban economy where the share of agricultural value added decreases in transition to the structure of the economy from agriculture to industry based. The descriptive statistics is presented in Table 2. Table 2 shows that there is significant variation in income inequality and per capita carbon emissions across countries.

As shown in Table 2, the share of pretax income earned by the richest 10% of the population ranges from 18 to 46% with the mean value of 32%. There are significant

Table 1 Summary of some of recent empirical findings on the relationship between income inequality and carbon emissions

Authors	Methodology	Sample countries	Period of analysis	Inequality measure	Relationship
Ravallion et al. (2000)	Pooled OLS	42 countries	1975–1992	Gini	Negative
Heerink et al. (2001)	Cross-sectional reg.	64 countries	1985	Gini	Negative
Borghesi (2006)	OLS and FE	37 countries	1988–1995	Gini	None (for FE)
Golley and Meng (2012)	Cross-sectional reg.	China	2005	Gini	Positive
Baek and Gweisah (2013)	ARDL	USA	1967–2008	Gini	Positive
Hao et al. (2016)	GMM	China	1995–2012	Gini	Positive
Jorgenson et al. (2017)	Time series cross-sectional Reg.	50 US states	1997–2012	Top 10% and Gini	Positive (using top10%), none (using Gini)
Hübler (2017)	Quantile regressions (QR) and FE	149 countries	1985–2012		Negative(for QR), none (for FE)
Grunewald et al. (2017)	Group FE	158 countries	1980–2008	Gini	Negative (low-income), Positive(for high-income economies)
Brännlund and Ghalwash (2008)	SURE	Sweden	1984, 1988, 1996		Concave
Clement and Meunie (2010)	FE	83 countries	1988–2003	Gini	Mixed
Guo (2014)	VECM	China	1978–2010	Gini, Theil	Negative
Kashwan (2017)		137 countries	1995–2005	Top 10%	Depends on democracy
Kasuga and Takaya (2017)	Cross-sectional reg.	Japan	1990–2012	(90th/10th)	Positive
Knight et al. (2017)	Time series cross-sectional Reg.	26 high-income countries	2000–2010	Wealth share of the top decile	Positive
Qu and Zhang (2011)	RE, GLS	36 countries	1980–1999	Median income	Negative
Wolde-Rufael and Idowu (2017)	Bounds test approach to cointegration	China, India	1971–2010	Gini	None
Zhang and Zhao (2014)	FE and FGLS	China	1995–2010	Gini	Positive

Table 2 Summary statistics, annual data (1945–2010, Observations = 1122)

Variable	Mean	SD	Min	Max
Top 10 income inequality (%)	31.5	4.8	18.0	46.4
Top 1 income inequality (%)	8.8	2.6	3.5	20.1
Gini coefficient (index)	29.0	4.3	18.3	43.0
CO ₂ emissions per capita (metric tons)	2.26	1.26	0.03	6.14
GDP per capita (International Geary–Khamis \$)	13367.0	6364.5	1346.13	31357.0
Population size ('000 at mid-year)	41169.52	55862.5	1688.0	309347.0
Share of agricultural value added (share of total)	0.07	0.07	0.01	0.56

variations in per capita CO₂ emissions across countries with standard deviation of 1.26.

3.2 Methodology

To examine the long-run effect of income inequality and economic growth on per capita carbon emissions, we employ panel cointegration analysis and dynamic common correlated effects based on mean group (CCEMG) estimators. Our econometric models address key features of cross-country panel data, such as heterogeneity, cross-sectional dependence and endogeneity. Before we proceed to the discussion of the long-run relationship between income inequality and carbon emissions, we briefly examine the time series properties of our data in Sect. 3.2.1.

3.2.1 Time series properties

In this section, we pretest for unit roots and cointegration as a prerequisite for panel cointegration analysis. For our long-run estimates to be consistent, the variables must be non-stationary and integrated of the same order. To test the stationarity of the variables and to ensure the robustness of the results, we employ several unit root tests that are widely used in the literature. Specifically, we use Levin et al. (2002) (LLC), Im et al. (2003) (IPS) and Pesaran (2007) (CIPS) unit root tests as they are the most commonly used unit root tests in the panel time series literature.

The LLC panel unit root test assumes homogeneous auto-regressive coefficients across countries. The null hypothesis in the LLC panel unit root test is that each time series contains a unit root, against the alternative hypothesis that no series contains a unit root (each series is stationary). The IPS panel unit root test relaxes the homogeneity assumption by allowing heterogeneous auto-regressive parameters. The IPS test statistic is the average of the individual Augmented Dickey Fuller statistics for N cross-section units and individual unit root tests. The null hypothesis in the IPS panel unit root test is that all series have a common unit root and the alternative hypothesis

Table 3 Panel unit root test results

Variables	Deterministic terms	LLC statistics	IPS statistics	CIPS statistics
<i>Levels</i>				
ln(per capita emission)	Constant, trend	-1.242	-0.989	-1.754
ln(gdp per capita)	Constant, trend	-0.037	1.333	-1.846
ln(top 10 %)	Constant, trend	-0.425	1.481	-2.419
ln(population size)	Constant, trend	-3.286***	-0.599	-2.002
ln(share of agriculture)	Constant, trend	-0.02	-0.592	-1.884
<i>First difference</i>				
ln(per capita emission)	Constant	-16.970***	-32.564***	-3.147***
ln(gdp per capita)	Constant	-23.678***	-29.45***	-3.340***
ln(top 10 %)	Constant	-22.022***	-24.494***	-3.282***
ln(population size)	Constant	-5.977***	-9.470***	-2.189**
ln(share of agriculture)	Constant	-19.05***	-29.367***	-3.079***

** and *** indicate rejection of the null at 5% and 1% significance levels, respectively. The critical values for the CIPS statistics with intercept and trend are -2.73 at 1% level and -2.92 at 5%, whereas the critical values with intercept only are -2.21 at 5% level and -2.40 at 1% level. Optimal lags are selected based on AIC for LLC and IPS statistics

allows for some series to be stationary. To account for cross-sectional dependence, we use the cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007). The CIPS test statistic is derived from cross-sectionally augmented ADF (CADF) tests, as a simple average of the individual CADF-tests. The null hypothesis for the CIPS test is that all time series in the panel contain a unit root, whereas the alternative hypothesis is a stationary process for at least one of the time series. The critical values for the CIPS test statistics are provided by Pesaran (2007) in Tables 2a–c.

Table 3 presents the unit root test results for our variables in levels and first differences. The LLC unit root test shows that only population size has no unit root while the null hypothesis of a unit root for other variables is rejected. Accounting for heterogeneity and cross-sectional dependence, the IPS and CIPS unit root tests cannot reject the null hypothesis that each series has a unit root in levels. The null of a unit process is rejected at the first differences for all variables. The rejections of the unit root hypotheses in first differences of the variables suggest that per capita carbon emissions, income inequality and GDP per capita are integrated of order 1, $I(1)$. The economic interpretation is that in the long-run, permanent changes in income inequality and per capita national income are associated with permanent changes in per capita carbon emissions.

Next, we apply the two-step procedure cointegration tests proposed by Pedroni (1999, 2004) and the four error-correction-based panel cointegration tests proposed by Westerlund (2007) to examine the existence of cointegration among inequality, national income and carbon emissions. The first step in Pedroni (1999, 2004) test involves an estimation using cointegrating regressions for each panel member, and the second step involves testing for stationarity of the estimated residuals. The coin-

Table 4 Panel cointegration test results

<i>Pedroni (1999, 2004)</i>				
	v	rho	t	adf
Panel test statistic	4.029***	-9.002***	-14.25***	-10.21***
Group test statistic		-8.483***	-16.31***	-12.79***
<i>Westerlund (2007)</i>				
	Gt	Ga	Pt	Pa
Test statistic value	-4.08***	-15.724***	-18.155***	-19.699***
Robust <i>p</i> value	0.000	0.000	0.000	0.000

All test statistics in Pedroni (1999, 2004) are distributed $N(0,1)$, under a null of no cointegration. ***indicates a rejection of the null hypothesis of no cointegration at 1% significance level. Optimal lags are determined by AIC

tegration tests reported in Table 4 show that the null hypothesis of no cointegration is rejected at 1% significance level.

The drawback of the residual-based cointegration tests of Pedroni (1999, 2004) is that they do not allow for common factor restrictions. In such cases, the tests may incorrectly fail to reject the null hypotheses of no cointegration. To account for this potential issue in the residual-based tests, we use error-correction-based panel cointegration tests proposed by Westerlund (2007) that allow for common factors. The tests are implemented by inferring whether the error-correction terms are zero as a test for the null of no cointegration. The error-correction-based panel cointegration tests allow for cross-sectional dependence and heterogeneity both in the long-run cointegrating relationship and in the short-run dynamics. The test results in Table 4 strongly reject the null hypothesis that the series are not cointegrated.

3.2.2 Econometric framework

To estimate the effect of income inequality on CO₂ emissions, we employ panel cointegration analysis and two-stage least square-based on dynamic common correlated effects mean group (CCEMG) estimators. To account for potential specification issues and to ensure that our results are robust, we use three econometric techniques: (i) the dynamic ordinary least square (DOLS) model that imposes slope homogeneity but corrects endogeneity biases that possibly arises from joint determination of income inequality and CO₂ emissions or from the variables and unobserved common factors; and (ii) the fully modified ordinary least square (FMOLS) as robustness check for the DOLS estimates; (iii) the CCEMG approach that allows for endogeneity, heterogeneity in slopes and cross-sectional dependence in errors.

In light of the gap in the existing literature on income inequality–carbon emissions nexus, addressing these specification issues is of paramount importance in our empirical analysis. Specifically, allowing for slope heterogeneity and cross-sectional dependence is critical as the effect of income inequality on per capita carbon emissions varies across countries and depends on country-specific factors. Our unique and long historical panel data set allows us to address these econometric issues by using

the dynamic CCEMG estimation technique. Equally important is the feedback effects and reverse causality from carbon emissions to inequality and economic development. The DOLS, FMOLS and CCEMG estimators allow for possible serial correlation and endogeneity of the regressors. Ignoring such econometric issues can result in biased and inconsistent estimates that may lead to spurious inferences about the inequality–emissions relationship.

Following Kao and Chiang (2000), our econometric specification for the estimation of the DOLS and FMOLS models is given by:

$$e_{it} = \alpha_i + \beta_1 \ln(I)_{it} + \beta_2 \ln(y)_{it} + \beta_3 [\ln(I)_{it} \times \ln(y)_{it}] + \beta_4 \ln(y^2)_{it} + X_{it} \boldsymbol{\gamma} + u_{it}, \quad (1)$$

where e , I and y and are per capita carbon emissions, income inequality and per capita income, respectively. X denotes the vector of control variables including the log of population, share of agricultural value added and lagged and lead values of the variables. i and t denote country and time indices, respectively. The parameters α_i are country-specific fixed effects that control for cross-country differences in time-invariant determinants of carbon emissions, inequality and economic development such as geography, history, culture, etc. All the variables are expressed in natural logarithms.

The DOLS estimators impose homogeneous slope coefficients over cross sections and impose cross-sectional independence in errors. These assumptions might be problematic as there are many common factors and exposures to common shocks (i.e., oil price shocks and global financial crises) that could lead to cross-sectional error dependencies. Failure to account for these issues may result in biased and inconsistent estimates. To overcome the potential specification issues in the DOLS estimator, we use dynamic CCEMG estimator proposed by Pesaran (2006) and Chudik and Pesaran (2015). The dynamic CCEMG estimator is based on auto-regressive distributive lag (ARDL) models augmented by cross-sectional averages that yields consistent estimates under the presence of cross-sectional dependence and unobserved common factors. The resulting estimates are robust to omitted variable and simultaneity bias. The dynamic CCEMG model for our case is specified as follows:

$$e_{it} = \lambda_i e_{i,t-1} + \beta_{1,i} \ln(I)_{it} + \beta_{2,i} \ln(y)_{it} + \beta_{3,i} [\ln(I)_{it} \times \ln(y)_{it}] + \beta_{4,i} \ln(y^2)_{it} + X_{it} \boldsymbol{\gamma}_i + \sum_{j=0}^p \delta_{ij} \bar{Z}_{i,t-j} + \varepsilon_{it}, \quad (2)$$

where $\bar{Z}_t = (\bar{e}_t, \bar{e}_{t-1}, \bar{I}_t, \bar{y}_t, \overline{(\ln(I) \times \ln(y))}_t, \bar{y}_t^2, \bar{X}_t)$ are the cross-sectional means, and ε_{it} are idiosyncratic errors distributed independently across i and t and are not correlated with unobserved common factors or regressors. The CCEMG estimates are computed as the average of individual coefficients: $\hat{\psi}_{MG} = \frac{1}{N} \sum_{i=1}^N \hat{\psi}_i$ with $\hat{\psi}_i = (\hat{\lambda}_i, \hat{\beta}_i, \hat{\gamma}_i)$.

Differentiating Eqs. (1) or (2) with respect to y and setting it to zero, we get the level of income that corresponds to the turning point of the EKC:

$$y = \exp\left(\frac{-(\beta_2 + \beta_3)}{2\beta_4}\right), \quad (3)$$

where β_2 is the coefficient of y , β_3 is the coefficient of the interaction term ($I \times y$), and β_4 is the coefficient of y^2 . Taking the derivative of emissions with respect to inequality yields the elasticity of emissions that depends on the level of per capita income. That is, $\frac{\partial e_{it}}{\partial I_{it}} = \beta_2 + \beta_3 \ln y_{it}$. The threshold level of income where the relationship between emissions and inequality changes from positive to negative is when,

$$\ln y = -\beta_2/\beta_3, \quad y^* = \exp(-\beta_2/\beta_3). \quad (4)$$

4 Empirical results and discussions

4.1 Results

In this section, we present our main results from the DOLS and FMOLS estimators that address endogeneity issues and the CCEMG estimates that account for heterogeneity and cross-sectional dependence. Our main empirical results are reported in Table 5.

As shown in the first row of Table 5, the coefficient of income share of the top 10% is positive and statistically significant across all specifications. The DOLS estimates show that a 1% increase in top income inequality is associated with about 4% increase in CO₂ emissions. The effect is quantitatively larger when we control for heterogeneity and cross-sectional dependence, as shown in column 7 of Table 5. The estimates from FMOLS model show similar effects of income inequality on carbon emissions. The FMOLS estimator yields statistically insignificant coefficient estimates for the GDP per capita and its squared term. This is likely due to the potential biases because the estimates depend on initial OLS estimation and nonparametric corrections. As indicated in Kao and Chiang (2000), the DOLS outperforms the FMOLS as the former requires neither initial estimation nor nonparametric correction.

The DOLS and CCEMG estimates show that national per capita income has a significant positive effect on carbon emissions, while the square of per capita income has a significant negative effect on emissions in line with EKC hypothesis. That is, economic development proxied by the log of GDP per capita is associated with more CO₂ emissions at initial stages of economic development and the effect is reversed after a certain threshold level of per capita GDP. Our findings are consistent with the hypothesis of environmental Kuznets curve (EKC) that suggests a concave relationship between environmental degradation and economic growth in the course of economic development. As shown in Table 5, the estimated turning point for the EKC is within the sample. The CCEMG estimate show that the EKC turning point is corresponding to a per capita income level of \$26,522. The figures from the DOLS estimates are smaller than that of the CCEMG estimate. With regard to the threshold level of per capita income where the relationship between emissions and inequality changes from positive to negative, the estimates from the homogeneous model show that the transition occurs at low level of per capita income which is within the sample. However, the estimates

Table 5 The effect of income inequality on CO₂ emissions—top 10%

	(1) <i>DOLS</i> $p = 1$	(2) $k = 2$	(3) $k = 3$	(4) <i>FMOLS</i> $k = 1$	(5) $k = 2$	(6) $k = 3$	(7) <i>CCEMG</i>
Income share of top 10 %	3.948** (1.756)	3.527** (1.785)	4.310** (1.878)	11.620* (6.766)	18.68** (7.408)	16.710** (8.191)	15.840** (4.013)
GDP per capita	6.227*** (0.818)	6.363*** (0.831)	5.781*** (0.874)	6.884** (2.778)	-2.561 (3.042)	-2.808 (3.363)	4.443** (1.885)
GDP per capita square	-0.375*** (0.043)	-0.382*** (0.044)	-0.364*** (0.046)	-0.464*** (0.135)	0.037 (0.148)	0.067 (0.164)	-0.210** (0.088)
GDP per capita \times top10%	-1.073*** (0.157)	-1.049*** (0.159)	-1.177*** (0.167)	-2.102*** (0.710)	-2.173*** (0.778)	-1.808** (0.860)	-0.165 (0.371)
Population size	0.827*** (0.263)	0.848*** (0.268)	0.899*** (0.281)	1.149*** (0.375)	0.393 (0.411)	0.218 (0.454)	-2.544** (1.201)
Population size \times top10%	0.610*** (0.094)	0.632*** (0.0954)	0.678*** (0.100)	0.924*** (0.332)	0.191 (0.364)	0.027 (0.402)	-1.580** (0.615)
Share of agricultural value added	-0.160*** (0.050)	-0.177*** (0.050)	-0.233*** (0.053)	-0.003 (0.150)	0.060 (0.164)	0.067 (0.182)	-0.043 (0.060)
Observations	1054	1037	986	1104	1104	1104	1054
Adjusted R^2	0.456	0.449	0.452	0.396	0.195	0.149	0.19
Threshold y	39.623	28.854	38.933	251.657	5412.198	10324	-
EKC turning point	964.876	1048.900	557.899	-	-	-	26521.590

The dependent variable is log of per capita carbon emissions. ** and *** indicate significance at the 5% and 1% levels, respectively. k denotes lag length. Robust standard errors in parentheses.

All variables are in natural logarithms. The EKC turning point and threshold level of y are calculated using Eqs. (3) and (4), respectively

Table 6 The effect of income inequality on CO₂ emissions—top 1%

	(1) <i>DOLS</i>	(2) <i>FMOLS</i>	(3) <i>CCEMG</i>
Income share of top 1 %	2.456** (1.071)	7.161* (3.659)	6.553** (2.971)
GDP per capita	3.119*** (0.995)	3.797 (2.832)	4.131** (2.098)
GDP per capita square	−0.231*** (0.051)	−0.328** (0.136)	−0.216** (0.106)
GDP per capita × top1%	−0.644*** (0.089)	−1.091*** (0.371)	−0.247 (0.232)
Population size	0.969*** (0.327)	0.913** (0.369)	−2.122* (1.243)
Population size × top1%	0.346*** (0.052)	0.322** (0.153)	−0.469 (0.370)
Share of agricultural value added	−0.151** (0.059)	−0.199 (0.155)	−0.093* (0.053)
Observations	870	1099	1046
Adjusted R^2	0.451	0.174	0.174
Threshold γ	45.316	708.892	−
EKC turning point	212.118	−	8028.402

The dependent variable is log of per capita carbon emissions. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses. The EKC turning point and threshold level of γ are calculated using Eqs. (3) and (4), respectively

from our preferred heterogeneous model indicate that the threshold does not exist as the coefficient of the interaction term is not statistically indistinguishable from zero.

Our findings on the effect of top income inequality on carbon emissions lend support to the findings of Jorgenson et al. (2017). As argued in Jorgenson et al. (2017), income share of the top 10% is more relevant for empirical analysis to test the hypothesis advanced in the political economy model and the emulation effect known as the Veblen effect. Using the US state level data, they find that income inequality measured by the income share of the richest 10% of the population is positively associated with CO₂ emissions. In line with the political economy approach, our results show that redistribution policies targeting the top income concentrations may have larger impacts on reducing carbon emissions.

As a robustness check, we use the top income inequality measured by the share of pretax income by the richest 1% of the population as an alternative measure of top income inequality. As shown in Table 6, the coefficient of the inequality measure is positive and statically significant, whereas the coefficient of the interaction term is negative and significant, confirming the robustness of our results.¹

¹ At the request of an anonymous referee, we also conduct a sensitivity check by excluding those countries rebuilding after World War II (WWII), including Germany, Japan, France, Netherlands, Italy and UK since our sample includes the period of WWII. Our results are robust to the exclusion of these countries.

Table 7 The effect of income inequality on CO₂ emissions—Gini coefficients

	(1) <i>DOLS</i>	(2) <i>FMOLS</i>	(3) <i>CCEMG</i>
Gini	− 8.240*** (1.962)	− 13.84** (5.780)	− 9.893*** (2.619)
GDP per capita	7.172*** (0.993)	5.563** (2.538)	8.529*** (2.266)
GDP per capita square	− 0.440*** (0.046)	− 0.473*** (0.118)	− 0.232** (0.095)
GDP per capita × Gini	0.456*** (0.167)	1.248** (0.509)	− 1.003** (0.424)
Population size	− 0.892** (0.447)	− 0.490 (1.017)	− 6.312*** (1.668)
Population size × Gini	0.304*** (0.104)	0.189 (0.301)	2.042*** (0.579)
Share of agricultural value added	− 0.173*** (0.054)	0.033 (0.139)	− 0.055 (0.052)
Observations	986	1104	1046
Adjusted R^2	0.461	0.514	0.127

The dependent variable is log of per capita carbon emissions. ** and *** indicate significance at the 5% and 1% levels, respectively. Robust standard errors in parentheses

In conclusion, both top income inequality and per capita national income have significant positive impact on per capita carbon emissions and account for a major part of the variations in carbon emissions. Our results are robust to various alternative econometric specifications confirming that our main conclusion holds. The square of per capita income has negative and significant effect on carbon emissions in line with environmental Kuznets curve hypothesis.

While the top income inequality is an important measure of income distribution, it does not capture changes in the middle of the income distribution. Specifically, the measure of top income inequality ignores how the poor are faring relative to the middle class. To address this issue, we use the Gini coefficients as measure of inequality to see how the results change and to compare with the literature that uses the Gini measure. We report the results in Table 7.

In contrast to the effects of top income inequality, the results in Table 7 show that income inequality measured in Gini coefficients has a negative association with carbon emissions. This result is consistent with the marginal propensity to emit approach. That is, as income inequality decreases in transition to middle-class society, the poor will increase their consumption of energy and other carbon-intensive energy inputs which in turn increases carbon dioxide emissions. Our findings of the negative association between the Gini index on carbon emissions are somewhat different from the findings of Jorgenson et al. (2017). They find that the Gini index has no statistically significant effect on carbon emissions, although the sign of the effect, in their case, is also negative,

whereas we find a statistically significant estimate of the effect of the Gini index on emissions. It appears that accounting for heterogeneity, cross-sectional dependence and feedback effects in our estimations yielded statistically stronger results compared to that of Jorgenson et al. (2017).² In addition, using long historical panel data set also allowed to obtain statistically significant estimates. Notably, our results on the effect of Gini coefficients on inequality support the findings of Ravallion et al. (2000) and Heerink et al. (2001) that document a trade-off between Gini index of inequality and carbon emissions.

Why the results differ for different measures of inequality? The two inequality measures capture different features of income distributions, which are useful to evaluate the arguments of different analytical approaches for emissions–inequality nexus. Specifically, the top income inequality better captures the political economy and emulative effects that explains a positive association between top income inequality and carbon emissions. On the other hand, the Gini index better captures the variations in income inequality that arises from the differences between low- and middle-income households that explains the negative effect of inequality on carbon emissions in line with the marginal propensity to emit approach. That is, an increase in inequality measured by the Gini index implies that a fall in demand by the poor for the energy-intensive goods due to lower incomes dominates the increase in demand stemming from the top income group.

4.2 What mechanisms explain the role of income inequality on carbon emissions

Linking our empirical results to the theoretical explanations, our findings suggest that economic and political factors are the main transmission mechanisms through which top income inequality affects the environment. The economic channel is driven by economic choice and behavior of individuals that results in aggregate environmental degradation. The political economy channel stipulates that concentration of wealth on the top of the income distribution influences implementation of environmental policy aimed at improving environmental quality.

Comparing our empirical findings to those of previous studies and theories discussed in the previous sections, our findings lend support to the theories proposed to analyze the complex relationship between income inequality and carbon emissions. In line with the approaches of the political economy and the emulative influence of the wealthy, an increase in the concentration of income in the top end of the distribution leads to an increase in carbon emissions. Our results support the findings of recent studies (Brännlund and Ghalwash 2008; Jorgenson et al. 2017; Knight et al. 2017). In addition, from the Keynesian perspective, lower-income households have a higher marginal propensity to consume than higher-income households. Thus, when inequality falls, the income levels of the poor increase, which due to the higher marginal propensity to consume results in a higher level of overall consumption,

² As Baltagi and Pesaran (2007) argued that the heterogeneous approach yields more sensible results than assuming homogeneous fixed time effects. Similarly, Coakley et al. (2006), based on a Monte Carlo study, show that, overall, the CCEMG estimator stands out as the most efficient and robust. Kao and Chiang (2000) show that DOLS and FMOLS methods allow for feedback effect in the estimations.

and thereby, in greater emissions. This mechanism in combination with the marginal propensity to emit approach, which postulates that the demand for energy-intensive goods increase with the level of disposable income, appears to explain the negative association between the Gini index and emissions.

While top income inequality is found to have a positive association with carbon emissions at lower level of economic development, its effect diminishes with increasing levels of per capita income. It is worth noting that increase in carbon emissions during the initial phase of the environmental Kuznets curve is more pronounced than the decrease in carbon emissions during the latter phase.

The possible reason for change in inequality–emission relationship from positive to negative as countries get richer could be skill-based technological revolution. That is, as countries get richer, they tend to invest in research and development (R&D) in the production of clean energy sources that reduces the carbon emissions and promotes ecological efficiency and outsource carbon-intensive industrial production to developing countries. As indicated in Gassebner et al. (2008), an increase in inequality is associated with a decrease in industrial sector in richer countries because of outsourcing of industrial production and the development of skill-biased technical change. This in turn reduces the political and emulative power of the rich to bloc measures aimed at reducing emissions. Another line of argument according to Scruggs (1998) is that an increase in income may be associated with a lower level of preference for environmental degradation if environment is a superior good. Further, our findings show that the Gini index of income inequality is negatively associated with carbon emissions in line with approaches of the marginal propensity to emit.

Compared to the previous studies on inequality and carbon emissions, this study utilizes improved data set for long period of time that allows us to estimate the long-run effect of inequality on the environment more precisely. One caveat to our study is that our sample does not include low-income countries, as top income inequality data are not sufficiently available for developing countries.

5 Concluding remarks

The relationship between income inequality and carbon emissions has occupied a central place in the environment and economic development literature. In this paper, we examine the long-run effect of income inequality and economic growth on per capita carbon emissions using long panel data and recent estimation techniques developed in panel time series literature that account for endogeneity, heterogeneity and cross-sectional dependence.

Our results indicate that an increase in top income inequality leads to a higher CO₂ emission, whereas an increase in the Gini index of inequality is negatively associated with CO₂ emission. Therefore, whether there is the trade-off between reducing inequality and controlling climate change depends on which inequality measure we use. Our results on the effect of top income inequality on carbon emissions show that there is no trade-off between achieving equality by redistribution policy and controlling climate change. On the other hand, the negative association between the Gini index of inequality and carbon emissions suggests a trade-off between promoting equality

and environmental quality. Further, our findings confirm that the relationship between national income and carbon emissions is concave, reinforcing the idea of environmental Kuznets curve hypothesis, which suggests a nonlinear relationship between economic development and quality of the environment.

From a policy perspective, our findings suggest that policies designed to promote social equity by reducing the concentration of top income inequality and long-run growth are likely to have a significant positive effect on environmental quality through the reduction in carbon emissions. Our results are in line with the political economy mechanisms suggested in the literature to explain the relationship between income inequality and CO₂ emissions. In light of this, redistribution policy approaches targeting income concentrations at the top of the distribution, such as higher marginal tax rate at the upper end and taxes on wealth, may help in reducing carbon emissions. Future research may focus on the transmission mechanisms through which income inequality transmits to carbon emissions.

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Compliance with ethical standards

Conflicts of interest All authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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