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The Impact of Income Inequality on Environmental Quality: A Sectoral-Level Analysis[1]

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Abstract

There is a growing literature on the relationship between income inequality and emissions. However, these studies ignore the sectoral level differences in carbon emissions. We argue that the environmental effect of inequality might vary at the sectoral level. Our main purpose is to contribute to this growing literature on the inequality-emissions nexus by considering sectoral-level differences. For that purpose, we focus on five different sectors: power industry, buildings, transport, other industrial combustion, and other sectors. To specify our model, we augment the environmental Kuznets curve framework with income inequality by controlling the effect of globalization and urbanization. Our country sample consists of 28 OECD economies for the period between 1990 and 2018. Methodologically, we apply the second-generation panel unit root, cointegration tests, and estimators, which produce robust results against the cross-sectional dependence. Our findings reveal that not only income but also income inequality is a crucial factor in explaining changes in sectoral emissions. While rising income inequality increases carbon emissions from the power and building sectors, this finding turns out to be negative for the transport, other industrial combustion, and other sectors. Our results suggest that policies aimed at reducing carbon emissions should be designed at the sectoral level.

Keywords Sectoral CO2 emissions, Income inequality, Environmental Kuznets Curve, Panel Data, OECD countries

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1. Introduction

Income inequality and climate change are two major threats faced by humankind in the twenty-first century. They undoubtedly play a key role in shaping our ecosystem and future. Therefore, both of them have gained significant attention from researchers and policymakers worldwide during the last decades. Recent model projections and data also confirm their importance. For example, according to the Intergovernmental Panel on Climate Change (IPCC) (Masson-Delmotte et al., 2018), global warming due to human activities might cause further changes in the climate system if global net anthropogenic carbon emissions have not been reduced by about 45% from 2010 levels by 2030. Similarly, absolute income disparities continue to increase. As shown in the United Nations (2020) report, the per capita income gap between high and low-income countries increased from 27,600$ to 42,800$ between 1990 and 2018. Therefore, reducing inequality within and among countries, which is integral to achieving the Sustainable Development Goals (SDGs), still remains a distant goal by 2030.

The simultaneous worsening of both income distribution and environmental outcomes raises the following question: Does there exist a relationship between these two indicators? Or, more specifically, does income inequality have significant implications for climate change? The answer to this question is regarded as highly important in the existing literature from the economic and environmental policy perspectives. It is because the balance of power between the poor and the rich is considered to have a substantial potential to determine the level of environmental degradation (Berthe & Elie, 2015; Borghesi, 2006; Boyce, 1994; Chen et al., 2020; Hailemariam et al., 2020; Ravallion et al., 2000). The importance of this issue is also strongly supported by recent data. According to the Oxfam report (Gore, 2020), while the richest 10% is responsible for 46% of total emissions growth, it is 49% and %6 for the middle 40% and the poorest 50%, respectively.

The theoretical arguments and empirical tests of the relationship between income inequality and environmental degradation date back to the mid-1990s (Berthe & Elie, 2015; Borghesi, 2000; Boyce, 1994; Cushing et al., 2015; Grunewald et al., 2017; Scruggs, 1998). Although findings generally confirm the strong link between these variables, a clear consensus regarding its sign has not yet been reached. While some scholars argue that there exists a negative or statistically

insignificant link between income inequality and carbon dioxide (CO2) emissions (Heerink et al., 2001; Ravallion et al., 2000; Scruggs, 1998), some others highlight the positive association and suggest that greater income inequality leads to more environmental deterioration (Boyce, 1994, 2007; Marsiliani & Renstroem, 2000; Torras & Boyce, 1998). Based on the vast literature on the inequality-emissions nexus, it can be concluded that the empirical estimates produce mixed results more likely due to the following reasons: *(i)* differences in the country sample, period, dataset, or econometric techniques (Borghesi, 2006; Clement & Meunie, 2010; Coondoo & Dinda, 2008; Grunewald et al., 2017; Mittmann & de Mattos, 2020; Morse, 2018; Zhu et al., 2018); *(ii)* the exclusion of some important explanatory variables from the model specification (Bai et al., 2020; Drabo, 2011; Kashwan, 2017; Kasuga & Takaya, 2017; You et al., 2020) *(iii)* the lack of reliable historical data (Atkinson & Brandolini, 2009; Berthe & Elie, 2015; Hailemariam et al., 2020; Uddin et al., 2020); and *(iv)* differences in data aggregation (Guo, 2014; Hao et al., 2016; Mushtaq et al., 2020; Zhang & Zhao, 2014).

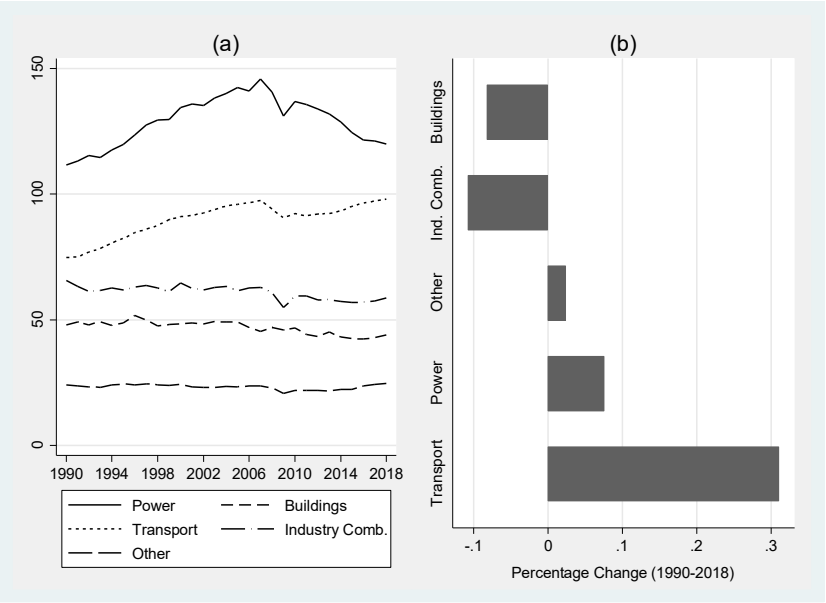
In this paper, we aim to contribute to this growing literature on the inequality-emissions nexus by considering sectoral-level differences for the first time. Put it differently, although the impact of economic inequality on environmental degradation has been examined by many researchers so far in the existing literature (Chen et al., 2020; Grunewald et al., 2017; Hailemariam et al., 2020; Yang et al., 2020), these country-level studies have mostly ignored the sectoral level differences in carbon emissions.[2] We argue that this highly preferred aggregated-level perspective might be one reason for obtaining conflicting results in the empirical literature and leading us to obtain conflicting results. This is because the share of sectoral emissions in total CO2 emissions in the countries significantly differs, implying that the contribution of each sector to the total carbon emissions of the country is not the same. Besides, while CO2 emissions in some sectors have a downward trend over time, this trend displays a worrying trend for others. Therefore, the impact of income inequality on sectoral emissions might vary.

The figures depicted in Figure 1 also strongly support our argument. While panel (a) of Figure 1 shows the evolution of sectoral CO2 emissions in the OECD countries over the period between 1990 and 2018, panel (b) calculates the percentage change for the same period. As can be seen in panel (a), the buildings and industrial combustion sectors have a downward trend over the whole

[2] For a detailed literature review, please see Section 2.

period. However, the power and transport sectors do not show the same gradual decline in emissions. Contrary to the buildings and industrial combustion sectors, the power and transport sectors have an increasing trend over the whole period. Although CO2 emissions of these two sectors decrease over the short period between 2007 and 2009, their current value in 2018 is still higher than in 1990. As shown in panel (b), while the percentage change in CO2 emissions between 1990 and 2018 is negative for the buildings and industrial combustion sectors, it is positive for the rest. Given this observation, assuming that the impact of income inequality on emissions is the same for all sectors does not seem to be a completely suitable approach to identify this link and prevents us from developing sector-specific strategies. Therefore, we consider that the environmental effect of income inequality is expected to vary from sector to sector. It is worth noting that some other studies also emphasize the importance of sectoral differences in emissions in the recent literature (Aslan et al., 2018; Erdoğan et al., 2020; Fatima et al., 2020; Karakaya et al., 2020; Khan et al., 2020; Lin & Xu, 2018; Morales-Lage et al., 2019; Sözen et al., 2016).

Figure 1 Sectoral CO2 emissions in the OECD countries (1990-2018) (expressed in metric units)



Source: Emissions Database for Global Atmospheric Research (EDGAR) (Crippa et al., 2019)

Given the premises above, we investigate the nexus between income inequality and CO2 emissions at the sectoral level. To this end, we perform an empirical analysis for five different

sectors: power industry, buildings, transport, other industrial combustion, and other sectors. To specify our model, we augment the well-known environmental Kuznets curve (EKC) framework with income inequality (Grossman & Krueger, 1991, 1995).[3] We also control the impact of globalization and urbanization on sectoral emissions (Inglesi-Lotz, 2019). Our country sample consists of 28 OECD economies[4] for the period between 1990 and 2018. We consider these countries deserve special interest from researchers and policymakers as they are the most important players in industrial production and trade, and take strong measures at different levels to mitigate CO2 emissions. Methodologically, we apply the second-generation panel unit root tests and estimators, which produce robust results against the cross-sectional dependence. The cross-sectional dependence test examines the existence of the endogenous change that occurred between cross-sections. The sustained results for cross-correlation of errors in the panel depend on the shape of the cross-dependence (Chudik et al., 2011). Besides, we test the slope homogeneity of model estimates for five sectors. We compare the weighted difference between the cross-sections and decide which assumption (homogeneity and heterogeneity) is implemented to estimate more powerful panel cointegration tests and estimators.

Our study contributes to the literature in three ways: First, to the best of our knowledge, it is the first study to empirically test the inequality-emissions nexus at the sectoral level. Second, as our model specification is based on the EKC framework, we can test the validity of the inverted U-shaped relationship between growth and emissions at the sectoral level, which is also rarely discussed in the literature (Amin et al., 2020; Aslan et al., 2018). Third, we use the second-generation panel data techniques to account for cross-sectional dependence. Besides, we choose cointegration tests and estimators allowing for heterogeneity in the slope parameters. Our findings reveal that the nexus between income inequality and emissions significantly vary across sectors. While income inequality has a statistically significant and positive effect on CO2 emissions from the power and building sectors, this effect is found to be negative for the transport, other industrial combustion, and other sectors.

The remainder of the paper is organized as follows. Section 2 provides a literature review on the nexus between income inequality and emissions. Section 3 introduces the data, model

[3] For further information regarding the EKC hypothesis, please see Section 3 or Aslan et al. (2019) and Ulucak et al. (2019).
[4] Please see section 3 for more information.

specification, and econometric framework. While Section 4 presents our empirical results, Section 5 concludes with policy implications.

2. Literature Review

Theoretically, several different mechanisms have been identified so far in the existing literature to explain the relationship between income inequality and environmental degradation. The first hypothesis is known as the political economy approach (Boyce, 1994, 2007; Torras & Boyce, 1998). According to this hypothesis, higher inequality results in a higher level of environmental degradation. This effect mainly occurs in two different ways, i.e., the rate of time preference and the cost-benefit analysis, and can be explained as follows: the wealthy class or the winners benefitting more from the environmentally degrading activities have a greater influence on environmental policies than the poor or the looser ones due to their economic and political power. As the relative power of the rich people increases the possibility of environmentally degrading activities, widening the income gap between groups harms the environment (Borghesi, 2006). Another study conducted by Marsiliani & Renstroem (2000) also theoretically confirms this positive link between inequality and emissions but in a different way. The main intuition behind the argument of Marsiliani & Renstroem (2000) is the distorted or less stringent environmental policies.

Scruggs (1998) opposes the arguments claimed by Boyce (1994) and Marsiliani & Renstroem (2000) by highlighting the differences in consumer preferences. Scruggs (1998) mainly argues that consumers prefer to use environmentally-friendly goods as their income rises. Therefore, unlike the hypotheses advanced by Boyce (1994) and Marsiliani & Renstroem (2000), the wealthy class is expected to increase their demand for a cleaner environment. As a consequence, rising income inequality reduces carbon emissions and contributes to environmental quality. This positive association between inequality and environmental quality is also shown by Ravallion et al. (2000) by paying a particular focus on the marginal propensity to emit (MPE).

The competing mechanisms theoretically explaining the inequality-emissions nexus (discussed above) have motivated many researchers to verify this link empirically. Consequently, since the early 2000s, the growing interest of scholars has made this discussion one of the highly-studied topics in the existing empirical literature. However, as stated earlier, a clear empirical consensus has not yet been reached. While some studies in the first strand support the arguments of Boyce

(1994), Marsiliani & Renstroem (2000), Torras & Boyce (1998) by reporting positive estimates for the relationship between inequality and emissions (Chen et al., 2020; Hailemariam et al., 2020; Knight et al., 2017; Ridzuan, 2019), some others highlight a negative or statistically insignificant linkage (Borghesi, 2006; Heerink et al., 2001; Huang & Duan, 2020; Hübler, 2017; Ravallion et al., 2000; Scruggs, 1998; Wolde-Rufael & Idowu, 2017). Panel (a) of Table 1 provides detailed information regarding these studies.

Table 1 Summary of literature review on the inequality-emissions nexus

Study	Sample & Period	Variables	Method	Finding
(a) country-level studies				
Magnani (2000)	19 OECD & 1980-1991	R&D expenditures for the environment & Gini	OLS, FE, RE	The widening income gap decreases environmental care
Heerink et al. (2001)	64 countries & 1985	CO2, SO2, SPM & Gini	Cross-section	Gini coefficient has a negative effect on CO2 emissions.
Padilla & Serrano (2006)	113 countries & 1971-1999	CO2 emissions & Gini	Decomposition	Income inequality is an important factor in explaining the changes in emissions
Coondoo & Dinda (2008)	88 countries & 1960-1990	SCR of emissions & LR of income	Cointegration	The effect of inequality is significant but differs based on country-groups
Holland et al. (2009)	50 countries (1975-1999)	Biodiversity loss & Gini	OLS	Inequality is an important determinant of biodiversity
Clement & Meunie (2010)	83 countries & 1988-2003	SO2 and organic water pollution & Gini	FE	The effect varies depending on environmental indicators used
Drabo (2011)	90 countries & 1970-2000	CO2, SO2, water pollution & Gini	FE, GMM, 2SLS	Institutions can mitigate the negative impact of inequality on the environment
Qu & Zhang (2011)	36 countries & 1980-1999	SO2, NOX & Gini	FGLS, RE	Improvement in inequality positively contributes to the environmental quality
Baek & Gweisah (2013)	USA & 1967-2008	CO2 emissions & Gini	ARDL	Equally distributed income yields better environmental quality
Grunewald et al. (2017)	158 countries & 1980-2008	CO2 emissions & Gini	OLS, FE	The direction of effect varies depending on the income level of countries
Hübler (2017)	149 countries & 1985-2012	CO2 emissions & Gini	Quantile regression	There exists a negative nexus between inequality and emissions.
Kashwan (2017)	137 countries	Protected areas & Gini, top 10%, top 10%-bottom 10%	Cross-section	Democracy is an important factor in the nexus between inequality and emission
Knight et al. (2017)	26 countries & 2000-2010	Consumption-based emissions & Wealth share of top 10%	FE	Wealth inequality positively contributes to the consumption-based CO2 emissions
Wolde-Rufael & Idowu (2017)	China, India & 1971 (1974)-2010	CO2 emissions & Gini	ARDL, DOLS, FMOLS	Income distribution is not an important factor in determining CO2 emissions
Morse (2018)	180 countries & 1995-2014	Environmental performance index & Gini	Cross-section	Environmental indicators play a key role in the inequality-environment nexus
Zhu et al. (2018)	BRICS & 1994-	CO2 emissions & Gini	Quantile regression	Inequality has a positive impact in

	2013			middle and high-emission countries
Ridzuan (2019)	174 countries & 1991-2010	SO2 & Gini	FE, DK	The rising income gap harms the environment.
Uzar & Eyuboglu (2019)	Turkey & 1984-2014	CO2 emissions & Gini	ARDL	There exists a positive link between inequality and emissions
Chen et al. (2020)	G20 & 1988-2015	CO2 emissions & Gini	Quantile regression	Higher inequality results in environmental degradation
Hailemariam et al. (2020)	17 OECD & 1945-2010	CO2 emissions & Top 10%, top 1%, Gini	DOLS, FMOLS, CCEMG	Income inequality increases CO2 emissions
Huang & Duan (2020)	92 countries & 1991-2015	CO2 emissions & Gini	Threshold regression	The impact of inequality on emissions is negative.
Mittmann & de Mattos (2020)	Latin American & 1970-2013	CO2 emissions & Gini	GMM	The sign of the inequality-emissions nexus depends on the income level
Yang et al. (2020)	47 countries & 1980-2016	CO2 emissions & Gini	DSUR	Inequality decreases the environmental deterioration in developing countries
You et al. (2020)	41 BRI & 1997-2012	CO2 emissions & Gini	SLM, SEM, SDM	Democracy is a significant factor in the nexus between inequality and emissions
Uddin et al. (2020)	G7 & 1870-2014	CO2 emissions & Gini	AMG, LLDVE	The effect of inequality on emissions vary depending on the period covered
(b) state, regional, or household level studies				
Boyce et al. (1999)	US states	Environmental stress index & Gini	OLS	Higher inequality results in greater environmental degradation
Brännlund & Ghalwash (2008)	Sweden & 1984, 1988, 1996	CO2, SO2, NOX & Gini	SUR	Environmental pollution is dependent on how income is distributed
Guo (2014)	Chinese regions 1978-2010	CO2 emission & Gini, Kakwani, Theil	VEC	There exists a trade-off between income distribution and emissions
Pattison et al. (2014)	US states & 2002	Consumption-based emissions & Median income	SLM	There exists a positive association between median income and emissions
Zhang & Zhao (2014)	Chinese provinces & 1995-2010	CO2 emissions & Gini	FE, PCSE, FGLS, DK	The link is greater in the Eastern regions of China
Jorgenson et al. (2015)	US states & 1990-2012	CO2 emissions & Theil	FE, RE	The impact of inequality on emissions is positive
Hao et al. (2016)	Chinese provinces & 1995-2012	CO2 emissions & Gini	GMM	Inequality is positively related to carbon emissions in the regions of China
Jorgenson et al. (2017)	US states & 1997-2012	CO2 emissions & Gini, top 10%	RE	The relationship varies depending on the inequality indicator used
Kasuga & Takaya (2017)	Japanese cities & 1990-2012	SO2, NOX, SPM & $95^{th}/5^{th}$, $90^{th}/10^{th}$, $80^{th}/20^{th}$	GMM	Inequality negatively affects environmental quality in some areas
Liu et al. (2019)	US states & 1997-2015	CO2 emissions & Top 10%	ARDL, Quantile	An increase in inequality results in higher emissions in the short-run
Q. Liu et al. (2019)	Chinese provinces & 1996-2014	CO2 emissions & Gini, Global Moran's I	FE	The rising income gap leads to environmental deterioration
Bai et al. (2020)	Chinese provinces & 2000-2015	CO2 emissions & Gini	FE, Threshold	Technological innovation is important to explore the correct link
Y. Liu et al. (2020)	China & 2010-2012-2014	CO2 emissions & Gini	FE	Inequality positively affects household carbon emissions

Mushtaq et al. (2020)	Chinese provinces & 1995-2015	CO2 emissions & Gini	FE, PCSE, FGLS	Innovation plays a key role in the link between inequality and emissions

Note: The abbreviations for methods are as follows. ARDL: the autoregressive distributed lag, FMOLS: the fully modified ordinary least squares, DOLS: the dynamic ordinary least squares, OLS: the ordinary least squares, FE: the fixed effects; RE: the random effects, CCEMG: the common correlated effects mean group, DSUR: the dynamic seemingly unrelated regression, FGLS: the feasible generalized least squares, 2SLS: the two-step least squares; AMG: the augmented mean group, LLDVE: the local linear dummy variable estimation, SLM: the spatial lag model, SEM: the spatial error model, SDM: the spatial Durbin model, DK: the Driscoll and Kraay non-parametric variance-covariance estimator, PCSE: the panel corrected the standard error, VEC: the vector error correction model, SUR: the seemingly unrelated regression. The abbreviations for country groups and variables are as follows. BRI: the Belt and Road Initiative, BRICS: Brazil, Russia, India, China, South Africa, G7: the group of seven, G20: the group of twenty, OECD: the Organization for Economic Co-operation and Development, SCR: the specific concentration ratio of emissions, LR: the Lorenz ratio of income.

As to the studies in the first strand, Magnani (2000) finds that the rising income gap reduces environmental care for the 19 OECD countries over the period between 1980 and 1991. Padilla & Serrano (2006) confirm this positive link between inequality and emissions for a longer time dimension, i.e., 1971-1999. The studies conducted by Clement & Meunie (2010), Drabo (2011), and Ridzuan (2019) use alternative indicators as a proxy for environmental degradation, such as Sulphur dioxide emissions (SO2) and organic water pollution. The results largely support the positive linkage once again for the larger country samples and highlight the sensitiveness of parameter estimates to the variable selection for the environmental quality (Morse, 2018). Similar findings are also reported by Holland et al. (2009), Qu & Zhang (2011), and Knight et al. (2017) for various environmental indicators, such as the proportion of threatened plant and vertebrate species, consumption-based CO2 emissions, and oxides of nitrogen (NOX) for different country samples. The existence of a positive linkage between income inequality and environmental degradation is robust even if alternative indicators as a proxy for income inequality (Coondoo & Dinda, 2008; Hailemariam et al., 2020; Kashwan, 2017; Magnani, 2000) or different estimators (Chen et al., 2020; Uddin et al., 2020; You et al., 2020; Zhu et al., 2018) have been used. Baek & Gweisah (2013) and Uzar & Eyuboglu (2019) confirm the positive impact of the Gini index on CO2 emission at the single country level, i.e., for the USA and Turkey, by using the autoregressive distributed lag (ARDL) technique. Some other studies highlight the importance of other factors, such as income level, geographical area, institutional quality, to identify the correct link between study variables (Coondoo & Dinda, 2008; Grunewald et al., 2017; Kashwan, 2017; Mittmann & de Mattos, 2020).

The empirical studies challenging the positive association between inequality and emissions also support their findings with alternative indicators, periods, methods, and country samples. The

cross-section analysis of Heerink et al. (2001) shows that while the Gini coefficient has a statistically significant and negative effect on CO2 emissions, it is statistically insignificant for SO2 and suspended particulate matter (SPM). Hübler (2017), Huang & Duan (2020), and Yang et al. (2020) confirm this negative linkage for different country groups by using alternative estimators. Wolde-Rufael & Idowu (2017) employ three different estimators to test the inequality-emissions nexus in China and India. The empirical results reveal that income distribution is not an important factor in explaining the changes in CO2 emissions.

It is equally important to note that all of the studies discussed above or shown in panel (a) of Table 1 have been conducted at the country-level, regardless of what they find about the direction of the link between income distribution and environmental quality. However, the studies in the literature are not only limited to these aggregated level studies. Some other papers also investigate the same nexus at the disaggregated level, such as at the regional or state level. Panel (b) of Table 1 reports these studies.

For the US states, while Boyce et al. (1999), Bouvier (2014), Pattison et al. (2014), Jorgenson et al. (2015), and Liu et al. (2019) find a positive association between inequality and emissions, Jorgenson et al. (2017) produce mixed results for different inequality measures. A recent study by Mader (2018) shows that alternative indicators, techniques, periods, and regions do not support the findings of Jorgenson et al. (2017). The empirical estimates of Kasuga & Takaya (2017) reveal a positive and statistically significant impact of inequality ($90^{th}/10^{th}$) on SO2, NOX, and SPM for Japanese cities in the residential and commercial areas. Based on the provincial panel data of China, Hao et al. (2016) emphasize the importance of regional differences in analyzing the link between income inequality and carbon emissions. Mushtaq et al. (2020) confirm the regional difference in China for the larger time-period by using alternative estimators and emphasizing the moderating role of innovation. Similar analyses are also performed for Chinese provinces by Golley & Meng (2012), Zhang & Zhao (2014), Guo (2014), Q. Liu et al. (2019), and Bai et al. (2020). Based on the Swedish household cross-sectional data, Brännlund & Ghalwash (2008) suggest that not only income but also income distribution is an important factor in explaining the changes in the environmental pollution in Sweden.

In summary, the current literature is unclear whether the impact of income distribution on environmental quality is positive or negative. While the vast majority of the empirical studies are

conducted at the country level, only a limited number of papers focus on the disaggregated data, such as the state or household level. Our study contributes to this growing literature by considering differences in sectoral CO2 emissions. To the best of our knowledge, no other study is available in the literature to investigate the link between income inequality and environmental degradation at the sectoral level for OECD countries. Therefore, this study is believed to offer a significant contribution to the literature.

3. Data Description, Model Specification, and Econometric Framework

3.1. Data Description

In this study, we investigate the nexus between income inequality (GINI) and CO2 emissions (CO2) at the sectoral level for the OECD countries.[5] The sectors covered in the study are the power industry (POW), buildings (BUI), transport (TRA), other industrial combustion (lnOIC), and other (OTH) sectors. In addition to income inequality, following the EKC framework, we have included gross domestic product (GDP) and the square of it (GDP^2) into our regressions as a determinant of sectoral emissions. We add two control variables, i.e., globalization (KOF), and urbanization (URB). We perform our empirical investigation for the period between 1990 and 2018. We present our variables and data sources in Table 2.

Table 2 Data description

Variables	Definition	Source
lnPOW	Carbon dioxide emissions of the power industry (Metric units per capita)	(Crippa et al., 2019)
lnBUI	Carbon dioxide emissions of the buildings (Metric units per capita)	(Crippa et al., 2019)
lnTRA	Carbon dioxide emissions of the transport (Metric units per capita)	(Crippa et al., 2019)
lnOIC	Carbon dioxide emissions of the other industrial combustion (Metric units per capita)	(Crippa et al., 2019)

[5] We perform our empirical investigation for the 28 OECD countries (Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States). We have excluded some countries from the sample due to data unavailability, especially for both income inequality and control variables.

lnOTH	Carbon dioxide emissions of the other sectors (Metric units per capita)	(Crippa et al., 2019)
lnGDP	GDP per capita (constant 2010 USD)	(WDI, 2020)
$lnGDP^2$	The square of GDP per capita (constant 2010 USD)	(WDI, 2020)
lnGINI	Gini coefficient of income inequality	(Solt, 2020)
lnKOF	The KOF globalization index	(Gygli et al., 2019)
lnURB	Urban Population (% total population)	(WDI, 2020)

Note: WDI denotes the World Bank's World Development Indicators. ln denotes the natural logarithm.

Table 3 Descriptive statistics

Variables	Observation	Mean	Std. Dev.	Min	Max
lnPOW	812	0.779	0.900	-2.377	2.336
lnBUI	812	0.120	0.703	-2.217	1.405
lnTRA	812	0.762	0.559	-0.725	2.740
lnOIC	812	0.468	0.544	-0.994	2.588
lnOTH	812	-0.355	0.458	-1.820	0.969
lnGDP	812	10.394	0.635	8.614	11.626
$lnGDP^2$	812	108.445	12.877	74.208	135.163
lnGINI	812	3.432	0.183	3.045	3.926
lnKOF	812	4.352	0.126	3.813	4.511
lnURB	812	4.343	0.137	3.869	4.585

Note: ln denotes the natural logarithm.

Tables 3 and 4 report the descriptive statistics and pair-wise correlation matrix for all the variables. As can be seen, there exist 812 observations for all variables. Explanatory variables have a low standard deviation that tends to be close to the mean. Dependent variables have a high standard deviation, indicating that their values expand over a broader range. CO2 emissions from the power industry are negatively correlated with all the variables, except for urbanization. However, in the building sector, income inequality and urbanization are negatively associated with CO2 emissions. CO2 emissions from transport, other industrial combustion, and other sectors are positively correlated to all the variables, except for income inequality. Besides, there is no strong correlation between explanatory variables. In short, the correlation between

independent variables and their determinants varies across the sectors, and there is no multicollinearity problem.

Table 4 Pairwise correlation matrix

Variables	lnGDP	$lnGDP^2$	lnGINI	lnKOF	lnURB
lnPOW	-0.052	-0.070	-0.018	-0.006	0.100
lnBUI	0.479	0.478	-0.501	0.384	-0.022
lnTRA	0.768	0.768	-0.367	0.473	0.343
lnOIC	0.443	0.444	-0.453	0.174	0.233
lnOTH	0.502	0.503	-0.545	0.190	0.131
lnGDP	1.000	-	-	-	-
$lnGDP^2$	0.99	1.000	-	-	-
lnGINI	-0.649	-0.646	1.000	-	-
lnKOF	0.753	0.745	-0.545	1.000	-
lnURB	0.295	0.294	-0.107	0.159	1.000

Note: ln denotes the natural logarithm.

3.2. Econometric Framework

The empirical investigation of this study consists of four parts. We first test the existence of the cross-sectional dependence of our study variables. To this end, we apply three different cross-sectional dependence tests. The first one is the Lagrange multiplier (LM) test developed by Breusch and Pagan (Breusch & Pagan, 1980). This test performs well when T is larger than N. However, it has substantial size distortions when N is large, and T is small. Pesaran (2004) overcomes this weakness and proposes the CD test designed for large N and small T panels. Therefore, we also apply the CD test of Pesaran (2004). The last one is the modified version of the LM test. The bias-adjusted LM test proposed by Pesaran et al. (2008) examines the sustainable power of exogenous regressors and normal errors in the panel. Therefore, it produces more robust results than the other cross-sectional dependence tests. Rejection of the null hypothesis for all three tests implies that the residuals are cross-sectionally dependent (Akın, 2019; Burdisso and Sangiácomo, 2016; De Hoyos and Sarafidis, 2006)).

Second, we examine the stationarity properties of data. As we find the cross-sectional dependence for all variables in the previous step of the empirical investigation, we perform the second-generation unit root tests considering cross-sectional dependence. We apply two unit root tests: bootstrap-IPS (Smith et al., 2004) and cross-sectionally augmented IPS (CIPS) (Pesaran, 2007). Both tests are based on the Augmented Dickey-Fuller (ADF) test. To consider cross-

sectional dependence, while Smith et al. (2004) improve the ADF test by limiting distribution in a bootstrap-based approach, Pesaran (2007) augments the ADF test with the cross-section averages of lagged levels and first-differences of the individual series. CIPS test is a factor modelling (FM) approach and assumes the presence of unobserved common factor. The null hypothesis of both tests is the existence of the unit root for the panel. It is worth noting that the CIPS test (especially the three-dimensional version) has a better power performance than the Bootstrap-IPS test if high levels of cross-sectional dependence exist in data (Giuletti, Otero and Smith, 2008: 191). We consider these issues when interpreting our unit root test results,

Thirdly, we investigate the cointegration relationship. To this end, we use the Westerlund (2007b) panel ECM cointegration approach. The panel cointegration test suggested by Westerlund (2007b) is a technique that is often used in the existing literature to analyze the long-run cointegration relationship. Westerlund (2007b) develop four different panel cointegration tests. All these tests consider cross-sectional dependence. The group-mean statistics (G_τ, G_α) are calculated under the heterogeneity assumption. Therefore, the alternative hypothesis of these tests is that at least one unit is cointegrated. On the other hand, the panel statistics (P_τ, P_α) are calculated under the homogeneity assumption. Thus, unlike the group-mean test statistics, the alternative hypothesis suggests that the panel is cointegrated as a whole (Persyn & Westerlund, 2008).

It is worth noting that G_α and P_α depend on T values. In other words, when the number of lags is large, normalization of G_α and P_α by T may lead to the Type I error (Westerlund, 2007b). In this study, we prefer to interpret G_τ and P_τ as our sample size large enough. We also examine the testing slope homogeneity of the panel with the Delta test (Pesaran & Yamagata, 2008) based on a standardized version of Swamy's test (Swamy, 1970) to decide test statistics (G_τ or P_τ).

In the fourth step, we estimate the long-run parameters. We employ three different estimators in the study: the group-mean panel-dynamic ordinary least-squares (DOLSMG) (Pedroni, 2001), the bias-adjusted OLS (BA-OLS) (Westerlund, 2007a), and the continuous updated fully modified (CUP-FM) (Bai & Kao, 2005).

DOLSMG estimator proposed by Pedroni (2001) is the augmented version of the individual time-series DOLS estimator. It can be applied to the nonstationary data showing the cointegrating

relationship between variables. This estimator has an important advantage for between-dimension panel time-series estimators in the case of slope heterogeneity (Neal, 2014; Pedroni, 2001). We, therefore, use the DOLSMG estimator for models 1, 2, and 3 (see section 3.3. for model specifications) as the slope parameters of these models are found to be heterogeneous. However, the delta test results confirm the slope homogeneity for models 4 and 5. Therefore, we estimate the long-run coefficients of these models with CUP-FM and BA-OLS estimators (Tatoğlu, 2020: 230-232).

The CUP-FM estimator uses the principal component and FM methods to calculate common factors and estimate the cointegrating vector. Besides, as this estimator assumes that the number of common factors is known, it significantly reduces the dimension of the cross-sectional correlation. The CUP-FM estimator thus performs well in small samples compared to the OLS. On the other hand, the BA-OLS uses several panel information criteria to estimate the number of factors. The simulation results show that the BA estimator outperforms in terms of precision and size accuracy (Bai & Kao, 2005; Westerlund, 2007a).

3.3. Model Specification

We investigate the nexus between CO2 emissions and income inequality under the well-known EKC framework (Grossman & Krueger, 1991; Panayotou, 1994). The EKC hypothesis mainly posits that as income rises in a country, it affects environmental quality negatively and harms the environment in the first stage. However, after reaching a certain income level (turning point), this negative impact diminishes, and environmental quality improves. Therefore, it suggests an inverted U-shaped relationship between environmental deterioration and income level (Bilgili et al., 2019).

Based on the EKC framework and following Chen et al. (2020), Hailemariam et al. (2020), Mushtaq et al. (2020), Torras & Boyce (1998), Wolde-Rufael & Idowu (2017), and many others, we specify our empirical model to be estimated in this study as follows

$$lnCO2_{it} = \beta_0 + \beta_1 lnGINI_{it} + \beta_2 lnGDP_{it} + \beta_3 ln(GDP_{it})^2 + \beta_4 lnKOF_{it} + \beta_5 lnURB_{it} + u_{it} \quad (1)$$

where while CO_2 is the dependent variable representing sectoral per capita CO2 emissions, $GINI$, GDP, and GDP^2 are our key independent variables and stand for income inequality, income per capita, and the square of income per capita, respectively. u_{it} is a disturbance term consisting of

country-specific fixed and time-variant effects. The subscripts i and t denote country and time period, respectively. In order to control the potential impact of other variables on sectoral CO_2, we added two control variables (KOF) and (URB) to our model specification: globalization (Inglesi-Lotz, 2019; Ulucak et al., 2020) and urbanization (Amin et al., 2020; You et al., 2020).[6] All series used in the estimates are in natural logarithm form in the estimations. It is worth noting that as we estimate Eq. (1) for five different sectors, we have five different models in the study. While models 1 and 2 correspond to the power industry (POW) and buildings sectors (BUI), models 3, 4, and 5 are for the transport (TRA), other industrial combustion (OIC), and other (OTH) sectors, respectively.

4. Empirical Results and Discussion

Before the empirical investigation of the relationship between inequality and emissions, we firstly test the existence of cross-sectional dependence among countries in the sample. The results are reported in Table 5. The findings reveal that the null hypothesis of independence among cross-sections is strongly rejected for all variables, implying the existence of dependence among cross-sections. It means that a shock occurring in one of the OECD countries might spill over into other economies. From the methodological perspective, this result helps us perform more appropriate tests and estimates in the following steps of the empirical investigation (Henningsen & Henningsen, 2019; Tugcu, 2018).

Table 5 Cross-Sectional Dependence Test

Variables	LM	LM_{adj}	CD
lnPOW	737.01*** (0.00)	13.06*** (0.00)	11.46*** (0.00)
lnBUI	1372.35*** (0.00)	36.16*** (0.00)	16.02*** (0.00)
lnTRA	926.34*** (0.00)	19.94*** (0.00)	19.17*** (0.00)
lnOIC	905.1*** (0.00)	19.17*** (0.00)	22.21*** (0.00)
lnOTH	915.84*** (0.00)	19.56*** (0.00)	19.80*** (0.00)
lnGDP	2501.31*** (0.00)	77.22*** (0.00)	43.42*** (0.00)
$lnGDP^2$	2528.33***	78.21***	43.88***

[6] For recent studies extending the EKC framework by adding control variables, please see Inglesi-Lotz (2019).

	(0.00)	(0.00)	(0.00)
lnGINI	827.84*** (0.00)	16.36*** (0.00)	3.60*** (0.00)
lnKOF	2202.97*** (0.00)	66.37*** (0.00)	39.65*** (0.00)
lnURB	3076.37*** (0.00)	98.14*** (0.00)	-1.61 (0.11)

Note: *** denotes cross-sectional dependence at the 1% level. Numbers in the parantheses ( ) are p-values.

After analyzing and confirming the cross-sectional dependence for all variables, we secondly test the stationarity properties of data. As all variables are cross-sectionally dependent, we apply the unit root tests allowing for cross-sectional dependence, known as the second-generation unit root tests in the literature. In doing so, we have performed two different unit root tests, i.e., $IPS_{bootstrap}$ and CIPS. The results are presented in Table 6. As can be seen, the unit root test results unveil a uniform order of integration for all variables. While the p-values of the variables for both unit root tests are generally found to be greater than 0.05 at the level, they are below 0.05 when the first difference of them is taken. It means that our study variables are not stationary at I(0). However, they turn out to be stationary at I(1). Therefore, a cointegration analysis seems ideal for further empirical analysis (Jalil & Rao, 2019).

Table 6 Unit root tests results

Variables	Level				First Difference			
	Constant		Constant & Trend		Constant		Constant & Trend	
	$IPS_{Bootstrap}$	CIPS	$IPS_{Bootstrap}$	CIPS	$IPS_{Boostrap}$	CIPS	$IPS_{Bootstrap}$	CIPS
lnPOW	-1.27 (0.84)	-0.78 (0.22)	-1.87 (0.89)	-1.02 (0.15)	-4.80*** (0.00)	-18.37*** (0.00)	-5.32*** (0.00)	-17.87*** (0.00)
lnBUI	-0.79 (0.98)	-1.69* (0.05)	-2.41 (0.17)	-3.82* (0.05)	-6.42*** (0.00)	-21.92*** (0.00)	-6.51*** (0.00)	-20.72*** (0.00)
lnTRA	-1.55 (0.38)	1.40 (0.92)	-1.92 (0.80)	-0.05 (0.48)	-3.88*** (0.00)	-16.51*** (0.00)	-4.20*** (0.00)	-14.74*** (0.00)
lnOIC	-1.29 (0.80)	-2.37 (0.00)	-2.28 (0.27)	-1.00 (0.16)	-5.28*** (0.00)	-19.41*** (0.00)	-5.40*** (0.00)	-18.07*** (0.00)
lnOTH	-1.63 (0.33)	-1.24 (0.11)	-2.11 (0.58)	0.21 (0.58)	-4.93*** (0.00)	-17.27*** (0.00)	-4.50*** (0.00)	-15.65*** (0.00)
lnGDP	-1.56 (0.44)	-0.53 (0.30)	-1.99 (0.67)	-1.60* (0.06)	-3.90*** (0.00)	-12.80*** (0.00)	-4.05*** (0.00)	-10.40*** (0.00)
$lnGDP^2$	-1.49 (0.52)	-0.35 (0.36)	-1.99 (0.67)	-1.44* (0.08)	-3.91 (0.00)	-12.72*** (0.00)	-4.05*** (0.00)	-10.29*** (0.00)
lnGINI	-1.86* (0.06)	0.69 (0.77)	-2.43 (0.10)	2.78 (0.99)	-3.14*** (0.00)	-8.98*** (0.00)	-3.38*** (0.00)	-7.03*** (0.00)
lnKOF	-3.69***	-1.01	-2.70**	-0.50	-4.36***	-18.87***	-4.97***	-17.42***

	(0.00)	(0.16)	(0.04)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)
lnURB	-1.82*** (0.01)	5.02 (1.00)	-2.05 * (0.09)	6.18 (1.00)	-1.81* (0.06)	-0.63 (0.73)	-2.71* (0.09)	-4.00*** (0.00)

Note: *, ** and *** denote the stationarity at the 10%, 5% and 1% levels. Numbers in the parentheses ( ) are p-values obtained based on 1000 replications. The maximum lag length is 3 in the Bootstrap IPS test.

As the integration order of all variables is one, we thirdly investigate whether sectoral CO2 emissions and their determinants are cointegrated or not in the long run. However, it is equally important to note that the selection of appropriate cointegration test and estimator largely depends on the homogeneity and cross-sectional dependence test results. Therefore, prior to the cointegration test, we first test the homogeneity and cross-sectional dependence for each model. The homogeneity and cross-sectional dependence test results are given in panel (a) of Table 7. The homogeneity test (Δ and Δ_{adj}) results show that the null hypothesis of homogeneity is rejected for models 1, 2, and 3, meaning that the slope coefficients are heterogeneous. On the other hand, the slope parameters are found to be homogenous in models 4 and 5. Besides, the test statistics of LM, LM_{adj}, and CD strongly reject the null of no cross-sectional dependence in line with our previous results for variables.

Table 7 Homogeneity, cross-sectional dependence, and cointegration test results for models

		(a) homogeneity and cross-sectional dependence tests				
Tests		Model 1	Model 2	Model 3	Model 4	Model 5
Δ		1.573 (0.11)	-1.762* (0.07)	2.97*** (0.00)	0.098 (0.92)	-0.094 (0.92)
Δ_{adj}		1.876* (0.06)	-2.100** (0.03)	3.54*** (0.00)	0.116 (0.90)	-0.112 (0.91)
LM		3306.52*** (0.00)	4711.21*** (0.00)	4246.19*** (0.00)	3345.36*** (0.00)	3062.90*** (0.00)
LM_{adj}		106.51*** (0.00)	157.60*** (0.00)	140.68*** (0.00)	107.92*** (0.00)	97.65*** (0.00)
CD		35.73*** (0.00)	40.89*** (0.00)	31.66*** (0.00)	19.57*** (0.00)	13.46*** (0.00)
		(b) cointegration test				
G_τ	Nothing	-26.61*** (0.00)	-12.91*** (0.00)	-4.90** (0.04)	-11.97*** (0.00)	-9.25**** (0.00)
	Constant	-53.31*** (0.00)	-14.10*** (0.00)	-7.36** (0.04)	-12.41** (0.00)	-9.67*** (0.00)
	Constant & Trend	-50.04 (0.14)	-15.04*** (0.00)	-12.54* (0.05)	-159.48 (0.32)	10.06*** (0.00)
P_τ	Nothing	-10.91* (0.06)	-7.12** (0.03)	-1.34 (0.46)	-2.53 (0.31)	-5.30*** (0.00)
	Constant	-20.63**	-6.88*	0.63	-6.04*	-6.55***

		(0.03)	(0.08)	(0.88)	(0.08)	(0.00)
	Constant & Trend	-41.28** (0.02)	-4.39 (0.32)	0.36 (0.83)	-34.68** (0.4)	-5.58 (0.09)

Note: *, ** and *** denote significance at 10%, 5% and 1%, respectively. For panel (a), numbers in the parentheses () are p-values obtained based on 800 replications. For panel (b), figures in the parentheses ( ) show p-values.

Given these outcomes, we perform a cointegration test considering the cross-sectional dependence and heterogeneity. To this end, we apply the Westerlund (Westerlund, 2007b) panel ECM cointegration approach as we find cross-sectional dependence in all models. The test results for each model are given in panel (b). As clearly seen, the results strongly reject the null hypothesis of no cointegration and verify the cointegration relationship between sectoral CO2 emissions, income, the square of income, income inequality, globalization, and urbanization in OECD countries.

Following the cointegration testing, we finally analyze the relationship between study variables by estimating the long-run parameters. To this end, we employ three different estimators, i.e., DOLSMG, BA-OLS, and CUP-FM. While the DOLSMG estimator performs well in the case of parameter heterogeneity, the BA-OLS and the CUP-FM estimators consider slope homogeneity.[7] The long-run parameter estimates of our models are presented in Table 8. Based on these findings, we obtain the following outcomes.

First of all, the nexus between income and emissions significantly vary across sectors. For example, we confirm the validity of the EKC hypothesis for the power and building sectors. As can be seen, while the relationship between income and CO2 emissions is statistically significant and positive for models 1 and 2 (8.982 and 13.23), it turns out to be negative for the square of income (-0.2709 and -0.6183). It means that rising income initially increases CO2 emissions from the power and building sectors in the OECD countries. However, after reaching a turning point, it reduces emissions in these sectors and positively contributes to the environment. The validity of the inverted U-shaped EKC hypothesis clearly shows us the importance of income level for mitigating emissions in these high-emitting sectors (see figure 1). Our finding is not consistent with Erdoğan et al. (2020), which find a statistically insignificant linkage for the selected G20

[7] In order to save space and report the estimation results in a concise manner, we do not report all estimation results in the main body. The BA-OLS and CUP-FM estimates of models 1-2-3 and the DOLSMG results for models 4-5 are also available from the authors upon request. Alternatively, an interested reader can see the supplementary file.

countries using the CCEMG and AMG estimators, more likely due to the differences in the study period, estimators, and country sample.

On the other hand, the inverted U-shaped relationship found for the power and building sectors does not hold for the transport sector. Although the DOLSMG results produce a positive and significant parameter estimate for the relationship between income and emissions in this sector (model 3) (8.023), the estimated coefficient of the square of income is not statistically significant in the same model (-0.2902). While this result is confirmed by Aslan et al. (2018) and Chandran & Tang (2013), it is not consistent with the findings of Amin et al. (2020) and Ozkan et al. (2019).

Similarly, the BA-OLS and CUP-FM estimates reject the validity of the inverted U-shaped EKC hypothesis for models 4 and 5. For example, as the estimated parameters of income and the square of income are, respectively, negative or statistically insignificant (-0.015, -0.003, -0.021, and -0.005) for model 5, this finding verifies a linearly decreasing growth-pollution association in the other sector (Sinha et al., 2019).

Table 8 The long-run parameter estimates

	Model 1	Model 2	Model 3	Model 4		Model 5	
	DOLSMG	DOLSMG	DOLSMG	BA-OLS	CUP-FM	BA-OLS	CUP-FM
lnGDP	8.982*** [7.286]	13.23*** [10.86]	8.023** [1.983]	-0.026*** [-4.158]	-0.018*** [-2.848]	-0.015*** [-2.617]	-0.021*** [-3.624]
$lnGDP^2$	-0.2709*** [-5.671]	-0.6183*** [-10.65]	-0.2902 [0.5421]	-0.026*** [-5.747]	-0.015*** [-3.384]	-0.003 [-0.933]	-0.005 [-1.435]
lnGINI	1.435*** [12.65]	1.451*** [9.088]	-0.0544*** [-3.489]	-0.069*** [-10.135]	-0.046*** [-6.708]	-0.028*** [-5.117]	-0.022*** [-4.036]
lnKOF	1.557*** [18.13]	0.3241*** [-4.105]	-1.267*** [-12.56]	-0.034*** [-6.190]	-0.018*** [-3.383]	-0.016*** [-3.042]	-0.016*** [-3.158]
lnURB	3.943*** [-4.598]	-6.832*** [-9.099]	1.286*** [10.95]	0.007 [1.498]	0.011** [2.148]	0.020*** [-2.885]	0.022*** [-3.222]

Note: *, ** and *** denote, respectively, statistically significance at the 10%, 5% and 1% levels. Figures reported in square brackets [ ] are t-statistics. Maximum lags length and leads are 1 for the DOLSMG estimates. The maximum common factor number is 2 for the BA-OLS and CUP-FM estimates.

Second, we find that income inequality has a heterogeneous effect on sectoral CO2 emissions. In other words, as shown in the third row of Table 8, the Gini coefficient has a statistically significant effect on emissions for all sectors, varying in terms of magnitude depending on the sector. However, while this effect is positive for the power and building sectors (models 1 and 2), it is found to be negative for the transport, other industrial combustion, and other sectors (models 3, 4, and 5). For example, the DOLSMG estimates reveal that a 1% increase in the Gini index

leads to an increase in emissions from the power and building sectors by about 1.4% (%1.435 and %1.451, respectively). On the other hand, three different estimates show that an increase in income inequality is negatively associated with CO2 emissions from transport (-0.054), other industrial combustion (-0.069 and -0.046), and other sectors (-0.028 and -0.022). Our positive estimates for the power and building sectors are in line with the political economy approach (Boyce, 1994, 2007; Marsiliani & Renstroem, 2000; Torras & Boyce, 1998), and many recent empirical studies in the existing literature (Chen et al., 2020; Hailemariam et al., 2020; Knight et al., 2017; Ridzuan, 2019). Therefore, it can be concluded that more equally distributed income might significantly reduce carbon emissions in the power and building sectors. Yet, this finding does not hold for the transport, other industrial combustion, and other sectors. The negative estimates for these sectors verify the arguments and findings of Scruggs (1998), Ravallion et al. (2000), Hübler (2017), Heerink et al. (2001), Huang & Duan (2020), and Wolde-Rufael & Idowu (2017), and suggest that environmental quality increases with a rising income gap in the OECD countries.

The empirical findings presented above, and observations depicted in Figure 1 clearly show us that the power, building, and transport sectors deserve special attention. In other words, these three sectors play a crucial role in determining the total CO2 emissions of the OECD countries due to their larger share in total carbon emissions. For example, the share of CO2 emissions from the power, building, and transport sectors is about 35%, 15%, and 25% over the years, respectively. More importantly, the percentage change in CO2 emissions between 1990 and 2018 is positive for the power and transport sectors (Crippa et al., 2019). When we combine this important information with our findings discussed above, the heterogeneous impact of income, the square of income, and income inequality on sectoral carbon emissions produce a highly interesting outcome for these sectors. For instance, we confirm the validity of the U-shaped EKC hypothesis for the power and building sectors, meaning that income level is an important factor affecting sectoral emissions. It is also equally important to note that the rise in emissions in the initial stages of the EKC curve is expected to be more pronounced than the decrease during the latter stages. We also find that improvements in income distribution might significantly reduce emissions in these sectors. Therefore, we can conclude that the reduction of emissions in the power and building sectors depends on income level and how income is distributed. In this

regard, policies to reduce carbon emissions in these sectors should be designed not only to increase income level but also to narrow the income gap.

On the other hand, the results reveal the opposite outcome for the transport sector. As can be seen, in line with the approach of the MPE (Ravallion et al., 2000), CO2 emissions from the transport sector reduces as income decreases or income equality rises. We should approach this result cautiously. As also stated by Scruggs (1998) and Mittmann & de Mattos (2020), this result does not necessarily imply that reducing income level or maintaining income inequality might significantly contribute to the environmental quality. It instead signals a challenge from the sustainability perspective for this sector. From this point of view, policies aimed at mitigating carbon emissions in the transport sector by reducing income inequality might not produce expected effective results for improving environmental outcomes. This also holds for the other industrial combustion and other sectors (Wolde-Rufael & Idowu, 2017).

Third, we discuss the results for other control variables, i.e., globalization and urbanization. As it is understood, the impact of globalization on sectoral emissions is statistically significant at the conventional significance level for all models. However, as also found for income inequality, this effect varies across the sectors. While the coefficient of globalization (lnKOF) is positive for models 1 and 2 (1.557 and 0.324), it is found to be negative for models 3, 4, and 5. It means that increased trade liberalization has a detrimental effect on the environmental quality as it increases CO2 emissions from the power and building sectors, implying a risk for the sustainability problem caused by these sectors. On the other hand, globalization has a negative effect on CO2 emissions from transport, other industrial combustion, and other sectors, indicating that trade openness contributes to the reduction of carbon emissions. Our negative estimates are compatible with Shahbaz et al. (2017), You & Lv (2018), M. Liu et al. (2020) in terms of the overall emission-globalization nexus.

Regarding the effect of urbanization on sectoral CO2 emissions, we find that urbanization is an important factor in explaining changes in CO2 emissions at the sectoral level. Except for the building sector, urbanization positively affects carbon emissions in all sectors, implying the negative role of urbanization on environmental quality. This result is not consistent with Amin et al. (2020), which find a statistically insignificant linkage between emissions and urbanization for

the transport sector in European countries. However, it is compatible with Xu & Lin (2015) confirming the significant effect of urbanization on China's transport sector.

5. Conclusion

A growing number of studies empirically investigate the inequality-emissions nexus in the literature. However, they ignore the sectoral differences in CO2 emissions. In this study, we mainly criticize this practice by showing the varying environmental effect of inequality across sectors. The sectors covered in the study are the power industry, buildings, transport, other industrial combustion, and other sectors. Our model specification is based on the well-known EKC framework. We perform our empirical investigation for the 28 OECD countries over the period between 1990 and 2018. Methodologically, we apply the second-generation panel unit root tests and estimators, which produce robust results against the cross-sectional dependence.

We obtain the following outcomes: *(i)* the cointegration test results confirm the long-run cointegration relationship between sectoral CO2 emissions, income, the square of income, income inequality, globalization, and urbanization in OECD countries; *(ii)* the parameter estimates find a statistically significant association between sectoral emissions and its determinants for almost all sectors; *(iii)* we confirm the validity of the EKC hypothesis for the power and building sectors, but not for the transport, other industrial combustion, and other sectors. While the effect of income on emissions from the transport sector is found to be positive, it is negative for the other industrial combustion and other sectors; *(iv)* income inequality has a heterogeneous effect on sectoral emissions. This effect is positive for the power and building sectors, whereas it is found to be negative for the transport, other industrial combustion, and other sectors; *(v)* as in the case of inequality, the effect of globalization varies across the sectors. Yet, except for the building sector, urbanization positively affects carbon emissions in all sectors.

This paper provides some policy recommendations to reduce sectoral CO2 emissions in OECD countries based on these findings. First, as it is clearly shown, not only income but also income distribution plays a key role in explaining the changes in sectoral emissions. Therefore, focusing particularly on policies designed to increase the income level might not be sufficient for controlling climate change and improving environmental quality. Policymakers should also pay appropriate attention to income distribution. Second, as the environmental effect of income inequality varies in terms of sign depending on the sector examined, designing sector-specific

policies seems to be a more suitable approach for improving environmental outcomes. For example, more equally distributed income might be beneficial for the power and building sectors to reduce CO2 emissions from these sectors as there is no trade-off between narrowing the income gap and achieving environmental goals. On the other hand, the negative link between inequality and emissions, especially for the high-emitting sectors, i.e., transport and other industrial combustion, confirms the trade-off and implies a big challenge from the sustainability perspective. In this regard, it is recommended that alternative policies should be formulated and implemented for these sectors. For example, increasing investment in renewable energy sources or facilitating the diffusion of technological development among all members might significantly reduce their contribution to total emissions. Third, in line with some other studies, observations and findings of this study for the transport sector produce worrying outcomes. Therefore, it is quite obvious that this sector deserves special attention by the governments. From this point of view, promoting sustainable transportation modes and increasing the environmental awareness of the urban population might significantly help to reduce CO2 emissions as a big part of transport emissions come from road vehicles.

Ethical Approval

All ethical standard has followed in this research paper. No formal approval is required.

Consent to Participate

The research is not on human and animal subjects.

Consent to Publish

We are willing to publish the research paper in Environmental Science and Pollution Research.

Authors Contributions

Sedat Alataş: Conceptualization, Writing – review & editing, Methodology. **Tuğba Akın:** Data curation, Software, Formal Analysis, Visualization.

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References

Akın, T. (2019). The effects of political stability on foreign direct investment in fragile five countries. *Central European Journal of Economic Modelling and Econometrics*, *11*(4), 234–255. https://doi.org/10.24425/cejeme.2019.131539

Amin, A., Altinoz, B., & Dogan, E. (2020). Analyzing the determinants of carbon emissions from transportation in European countries: the role of renewable energy and urbanization. *Clean Technologies and Environmental Policy*, *22*(8), 1725–1734. https://doi.org/10.1007/s10098-020-01910-2

Aslan, A., Destek, M. A., & Okumus, I. (2018). Sectoral carbon emissions and economic growth in the US: Further evidence from rolling window estimation method. *Journal of Cleaner Production*, *200*, 402–411. https://doi.org/10.1016/j.jclepro.2018.07.237

Aslan, A., Dogan, E., & Altinoz, B. (2019). Single-Country Versus Multiple-Country Studies. In *Environmental Kuznets Curve (EKC)* (pp. 25–36). Elsevier. https://doi.org/10.1016/b978-0-12-816797-7.00004-7

Atkinson, A. B., & Brandolini, A. (2009). On data: A case study of the evolution of income inequality across time and across countries. *Cambridge Journal of Economics*, *33*(3), 381–404. https://doi.org/10.1093/cje/bel013

Baek, J., & Gweisah, G. (2013). Does income inequality harm the environment?: Empirical evidence from the United States. *Energy Policy*, *62*, 1434–1437. https://doi.org/10.1016/j.enpol.2013.07.097

Bai, C., Feng, C., Yan, H., Yi, X., Chen, Z., & Wei, W. (2020). Will income inequality influence the abatement effect of renewable energy technological innovation on carbon dioxide emissions? *Journal of Environmental Management*, *264*(March), 110482. https://doi.org/10.1016/j.jenvman.2020.110482

Bai, & Kao, C. (2005). On the estimation and inference of a panel cointegration model with cross-sectional dependence. In B. H. Baltagi (Ed.), *Contributions to Economic Analysis* (Issue 75, pp. 3–30). https://doi.org/10.1016/S0573-8555(06)74001-9

Berthe, A., & Elie, L. (2015). Mechanisms explaining the impact of economic inequality on environmental deterioration. *Ecological Economics*, *116*, 191–200. https://doi.org/10.1016/j.ecolecon.2015.04.026

Bilgili, F., Muğaloğlu, E., Kuşkaya, S., Bağlıtaş, H. H., & Gençoğlu, P. (2019). Most Up-to-Date Methodologic Approaches. In *Environmental Kuznets Curve (EKC)* (pp. 115–139). Elsevier. https://doi.org/10.1016/b978-0-12-816797-7.00010-2

Borghesi, S. (2000). *Income inequality and the environmental Kuznets curve* (No. 83).

Borghesi, S. (2006). Income inequality and the environmental Kuznets curve. *Environment, Inequality and Collective Action*, *33*.

Bouvier, R. (2014). Distribution of income and toxic emissions in Maine, United States: Inequality in two dimensions. *Ecological Economics*, *102*, 39–47. https://doi.org/10.1016/j.ecolecon.2014.03.005

Boyce, J. K. (1994). Inequality as a cause of environmental degradation. *Ecological Economics*, *11*(3), 169–178. https://doi.org/10.1016/0921-8009(94)90198-8

Boyce, J. K. (2007). Is inequality bad for the environment? *Research in Social Problems and Public Policy*, *15*(135), 267–288. https://doi.org/10.1016/S0196-1152(07)15008-0

Boyce, J. K., Klemer, A. R., Templet, P. H., & Willis, C. E. (1999). Power distribution, the environment, and public health: A state-level analysis. *Ecological Economics*, *29*(1), 127–140. https://doi.org/10.1016/S0921-8009(98)00056-1

Brännlund, R., & Ghalwash, T. (2008). The income-pollution relationship and the role of income distribution: An analysis of Swedish household data. *Resource and Energy Economics*, *30*(3), 369–387. https://doi.org/10.1016/j.reseneeco.2007.11.002

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, *47*(1), 239.

https://doi.org/10.2307/2297111

Burdisso, T., & Sangiácomo, M. (2016). Panel Time Series: Review of the Methodological Evolution. *Stata Journal*, *16*(2), 424–442. https://doi.org/10.1177/1536867X1601600210

Chandran, V. G. R., & Tang, C. F. (2013). The impacts of transport energy consumption, foreign direct investment and income on CO2 emissions in ASEAN-5 economies. *Renewable and Sustainable Energy Reviews*, *24*, 445–453. https://doi.org/10.1016/j.rser.2013.03.054

Chen, J., Xian, Q., Zhou, J., & Li, D. (2020). Impact of income inequality on CO2 emissions in G20 countries. *Journal of Environmental Management*, *271*(May). https://doi.org/10.1016/j.jenvman.2020.110987

Chudik, A., Pesaran, M. H., & Tosetti, E. (2011). Weak and strong cross-section dependence and estimation of large panels. *The Econometrics Journal*, *14*(1), C45–C90. https://doi.org/10.1111/j.1368-423X.2010.00330.x

Clement, M., & Meunie, A. (2010). Is Inequality Harmful for the Environment? An Empirical Analysis Applied to Developing and Transition Countries. In *Review of Social Economy* (Vol. 68, Issue 4). https://doi.org/10.1080/00346760903480590

Coondoo, D., & Dinda, S. (2008). Carbon dioxide emission and income: A temporal analysis of cross-country distributional patterns. *Ecological Economics*, *65*(2), 375–385. https://doi.org/10.1016/j.ecolecon.2007.07.001

Crippa, M., Oreggioni, G., Guizzardi, D., Muntean, M., Schaaf, E., Lo Vullo, E., Solazzo, E., Monforti-Ferrario, F., Olivier, J. G. J., & Vignati, E. (2019). Fossil CO2 and GHG emissions of all world countries. In *Luxemburg: Publication Office of the European Union*. https://doi.org/10.2760/687800, JRC117610

Cushing, L., Morello-Frosch, R., Wander, M., & Pastor, M. (2015). The haves, the have-nots, and the health of everyone: The relationship between social inequality and environmental quality. *Annual Review of Public Health*, *36*, 193–209. https://doi.org/10.1146/annurev-publhealth-031914-122646

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *Stata Journal*, *6*(4), 482–496. https://doi.org/10.1177/1536867x0600600403

Drabo, A. (2011). Impact of income inequality on health: Does environment quality matter? *Environment and Planning A*, *43*(1), 146–165. https://doi.org/10.1068/a43307

Erdoğan, S., Yıldırım, S., Yıldırım, D. Ç., & Gedikli, A. (2020). The effects of innovation on sectoral carbon emissions: Evidence from G20 countries. *Journal of Environmental Management*, *267*(December 2019), 1–10. https://doi.org/10.1016/j.jenvman.2020.110637

Fatima, T., Karim, M. Z. abd, & Meo, M. S. (2020). Sectoral CO2 emissions in China: asymmetric and time-varying analysis. *Journal of Environmental Planning and Management*, *64*(4), 581–610. https://doi.org/10.1080/09640568.2020.1776691

Golley, J., & Meng, X. (2012). Income inequality and carbon dioxide emissions: The case of Chinese urban households. *Energy Economics*, *34*(6), 1864–1872. https://doi.org/10.1016/j.eneco.2012.07.025

Gore, T. (2020). *Confronting Carbon Inequality* (Issue September).

Grossman, G., & Krueger, A. (1991). Environmental Impacts of a North American Free Trade Agreement. *National Bureau of Economic Research*, *3914*. https://doi.org/10.3386/w3914

Grossman, G., & Krueger, A. (1995). Economic Growth and the Environment. *The Quarterly Journal of Economics*, *110*(2), 353–377.

Grunewald, N., Klasen, S., Martínez-Zarzoso, I., & Muris, C. (2017). The Trade-off Between Income Inequality and Carbon Dioxide Emissions. *Ecological Economics*, *142*, 249–256. https://doi.org/10.1016/j.ecolecon.2017.06.034

Giulietti, M., Otero, J., & Smith, J. (2008). Testing for unit roots in three-dimensional heterogeneous panels in the presence of cross-sectional dependence. *Economics Letters*, *101*(3), 188-192.

Guo, L. (2014). CO2 Emissions and regional income disparity: Evidence from China. *Singapore Economic Review*, *59*(1). https://doi.org/10.1142/S0217590814500076

Gygli, S., Haelg, F., Potrafke, N., & Sturm, J. E. (2019). No Title. *The Review of International Organizations*, *14*, 543–574. https://doi.org/https://doi.org/10.1007/s11558-019-09344-2

Hailemariam, A., Dzhumashev, R., & Shahbaz, M. (2020). Carbon emissions, income inequality

and economic development. *Empirical Economics*, *59*(3), 1139–1159. https://doi.org/10.1007/s00181-019-01664-x

Hao, Y., Chen, H., & Zhang, Q. (2016). Will income inequality affect environmental quality? Analysis based on China's provincial panel data. *Ecological Indicators*, *67*, 533–542. https://doi.org/10.1016/j.ecolind.2016.03.025

Heerink, N., Mulatu, A., & Bulte, E. (2001). Income inequality and the environment: Aggregation bias in environmental Kuznets curves. *Ecological Economics*, *38*(3), 359–367. https://doi.org/10.1016/S0921-8009(01)00171-9

Henningsen, A., & Henningsen, G. (2019). Analysis of panel data using R. In *Panel Data Econometrics: Theory*. https://doi.org/10.1016/B978-0-12-814367-4.00012-5

Holland, T. G., Peterson, G. D., & Gonzalez, A. (2009). A cross-national analysis of how economic inequality predicts biodiversity loss. *Conservation Biology*, *23*(5), 1304–1313. https://doi.org/10.1111/j.1523-1739.2009.01207.x

Huang, Z., & Duan, H. (2020). Estimating the threshold interactions between income inequality and carbon emissions. *Journal of Environmental Management*, *263*(March), 110393. https://doi.org/10.1016/j.jenvman.2020.110393

Hübler, M. (2017). The inequality-emissions nexus in the context of trade and development: A quantile regression approach. *Ecological Economics*, *134*, 174–185. https://doi.org/10.1016/j.ecolecon.2016.12.015

Inglesi-Lotz, R. (2019). Recent Studies (Extending Basic Environmental Kuznets Curve Model by Adding More Variables). In *Environmental Kuznets Curve (EKC)* (pp. 15–23). Elsevier. https://doi.org/10.1016/b978-0-12-816797-7.00003-5

Jalil, A., & Rao, N. H. (2019). Time Series Analysis (Stationarity, Cointegration, and Causality). In *Environmental Kuznets Curve (EKC)* (pp. 85–99). Elsevier. https://doi.org/10.1016/b978-0-12-816797-7.00008-4

Jorgenson, A. K., Schor, J. B., Huang, X., & Fitzgerald, J. (2015). Income inequality and residential carbon emissions in the United States: A preliminary analysis. *Human Ecology Review*, *22*(1), 93–105. https://doi.org/10.22459/HER.22.01.2015.06

Jorgenson, A., Schor, J., & Huang, X. (2017). Income Inequality and Carbon Emissions in the United States: A State-level Analysis, 1997–2012. *Ecological Economics*, *134*, 40–48. https://doi.org/10.1016/j.ecolecon.2016.12.016

Karakaya, E., Alataş, S., & Yılmaz, B. (2020). Sectoral convergence in energy consumption from developing country perspective: The case of Turkey. *Energy Efficiency*, *13*(7), 1457–1472. https://doi.org/10.1007/s12053-020-09891-3

Kashwan, P. (2017). Inequality, democracy, and the environment: A cross-national analysis. *Ecological Economics*, *131*, 139–151. https://doi.org/10.1016/j.ecolecon.2016.08.018

Kasuga, H., & Takaya, M. (2017). Does inequality affect environmental quality? Evidence from major Japanese cities. *Journal of Cleaner Production*, *142*, 3689–3701. https://doi.org/10.1016/j.jclepro.2016.10.099

Khan, A. N., En, X., Raza, M. Y., Khan, N. A., & Ali, A. (2020). Sectorial study of technological progress and CO2 emission: Insights from a developing economy. *Technological Forecasting and Social Change*, *151*(December 2019), 119862. https://doi.org/10.1016/j.techfore.2019.119862

Knight, K. W., Schor, J. B., & Jorgenson, A. K. (2017). Wealth Inequality and Carbon Emissions in High-income Countries. *Social Currents*, *4*(5), 403–412. https://doi.org/10.1177/2329496517704872

Lin, B., & Xu, B. (2018). Factors affecting CO2 emissions in China's agriculture sector: A quantile regression. *Renewable and Sustainable Energy Reviews*, *94*(April), 15–27. https://doi.org/10.1016/j.rser.2018.05.065

Liu, C., Jiang, Y., & Xie, R. (2019). Does income inequality facilitate carbon emission reduction in the US? *Journal of Cleaner Production*, *217*, 380–387. https://doi.org/10.1016/j.jclepro.2019.01.242

Liu, M., Ren, X., Cheng, C., & Wang, Z. (2020). The role of globalization in CO2 emissions: A semi-parametric panel data analysis for G7. *Science of the Total Environment*, *718*, 137379. https://doi.org/10.1016/j.scitotenv.2020.137379

Liu, Q., Wang, S., Zhang, W., Li, J., & Kong, Y. (2019). Examining the effects of income

inequality on CO2 emissions: Evidence from non-spatial and spatial perspectives. *Applied Energy*, *236*(February 2018), 163–171. https://doi.org/10.1016/j.apenergy.2018.11.082

Liu, Y., Zhang, M., & Liu, R. (2020). The impact of income inequality on carbon emissions in china: A household-level analysis. *Sustainability (Switzerland)*, *12*(7), 1–22. https://doi.org/10.3390/su12072715

Mader, S. (2018). The nexus between social inequality and CO2 emissions revisited: Challenging its empirical validity. *Environmental Science and Policy*, *89*(August), 322–329. https://doi.org/10.1016/j.envsci.2018.08.009

Magnani, E. (2000). The Environmental Kuznets Curve, environmental protection policy and income distribution. *Ecological Ec*, *32*, 431–443. https://doi.org/https://doi.org/10.1016/S0921-8009(99)00115-9

Marsiliani, L., & Renstroem, T. I. (2000). Inequality, Environmental Protection and Growth. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.235083

Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., Pirani, A., Moufouma-Okia, W., Péan, C., & Pidcock, R. (2018). Summary for policymakers. *Global Warming Of*, *1*, 1–32.

Mittmann, Z., & de Mattos, E. J. (2020). Income Inequality and Carbon Dioxide Emissions: Evidence From Latin America. *Journal of International Development*, *32*(3), 389–407. https://doi.org/10.1002/jid.3459

Morales-Lage, R., Bengochea-Morancho, A., Camarero, M., & Martínez-Zarzoso, I. (2019). Club convergence of sectoral CO2 emissions in the European Union. *Energy Policy*, *135*(September), 111019. https://doi.org/10.1016/j.enpol.2019.111019

Morse, S. (2018). Relating Environmental Performance of Nation States to Income and Income Inequality. *Sustainable Development*, *26*(1), 99–115. https://doi.org/10.1002/sd.1693

Mushtaq, A., Chen, Z., Ud Din, N., Ahmad, B., & Zhang, X. (2020). Income inequality, innovation and carbon emission: Perspectives on sustainable growth. *Economic Research-Ekonomska Istrazivanja* , *33*(1), 769–787. https://doi.org/10.1080/1331677X.2020.1734855

Neal, T. (2014). *Panel cointegration analysis with xtpedroni*. *3*, 684–692. https://doi.org/10.1177/1536867X1401400312

Ozkan, T., Yanginlar, G., & Kalayci, S. (2019). Testing the transportation-induced environmental Kuznets curve hypothesis: Evidence from eight developed and developing countries. *International Journal of Energy Economics and Policy*, *9*(1), 174–183. https://doi.org/10.32479/ijeep.7330

Padilla, E., & Serrano, A. (2006). Inequality in CO2 emissions across countries and its relationship with income inequality: A distributive approach. *Energy Policy*, *34*(14), 1762–1772. https://doi.org/10.1016/j.enpol.2004.12.014

Panayotou, T. (1994). Empirical tests and policy analysis of environmental degradation at different stages of economic development. In *Pacific and Asian Journal of Energy* (Vol. 4, Issue 1).

Pattison, A., Habans, R., & Clement, M. T. (2014). Ecological Modernization or Aristocratic Conservation? Exploring the Impact of Affluence on Carbon Emissions at the Local Level. *Society and Natural Resources*, *27*(8), 850–866. https://doi.org/10.1080/08941920.2014.911996

Pedroni, P. (2001). Purchasing power parity tests in cointegrated panels. *Review of Economics and Statistics*, *83*(4), 727–731. https://doi.org/10.1162/003465301753237803

Persyn, D., & Westerlund, J. (2008). Error-correction – based cointegration tests for panel data. *The Stata Journal*, *8*(2), 232–241.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *The Econometrics Journal*, *11*(1), 105–127. https://doi.org/10.1111/j.1368-423X.2007.00227.x

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Qu, B., & Zhang, Y. (2011). Effect of income distribution on the environmental Kuznets curve. *Pacific Economic Review*, *16*(3), 349–370. https://doi.org/10.1111/j.1468-0106.2011.00552.x

Ravallion, M., Heil, M., & Jalan, J. (2000). Carbon emissions and income inequality. *Oxford Economic Papers*, *52*(4), 651–669. https://doi.org/10.1093/oep/52.4.651

Ridzuan, S. (2019). Inequality and the environmental Kuznets curve. *Journal of Cleaner Production*, *228*, 1472–1481. https://doi.org/10.1016/j.jclepro.2019.04.284

Scruggs, L. A. (1998). Political and economic inequality and the environment. *Ecological Economics*, *26*(3), 259–275. https://doi.org/10.1016/S0921-8009(97)00118-3

Shahbaz, M., Khan, S., Ali, A., & Bhattacharya, M. (2017). The Impact of Globalization On Co2 Emissions in China. *Singapore Economic Review*, *62*(4), 929–957. https://doi.org/10.1142/S0217590817400331

Sinha, A., Shahbaz, M., & Balsalobre, D. (2019). Data Selection and Environmental Kuznets Curve Models - Environmental Kuznets Curve Models, Data Choice, Data Sources, Missing Data, Balanced and Unbalanced Panels. In *Environmental Kuznets Curve (EKC)* (pp. 65–83). Elsevier. https://doi.org/10.1016/b978-0-12-816797-7.00007-2

Smith, L. V., Leybourne, S., Kim, T. H., & Newbold, P. (2004). More powerful panel data unit root tests with an application to mean reversion in real exchange rates. *Journal of Applied Econometrics*, *19*(2), 147–170. https://doi.org/10.1002/jae.723

Solt, F. (2020). Measuring income inequality across countries and over time: The standardized world income inequality database. *Social Science Quarterly*, *101*(3), 1183–1199. https://doi.org/10.1111/ssqu.12795

Sözen, A., Cakir, M. T., & Cipil, F. (2016). Sectoral CO 2 emission reductions in Turkey: Preparing for Doha 2020. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, *38*(7), 905–913. https://doi.org/10.1080/15567036.2013.850559

Swamy, P. A. V. B. (1970). Efficient Inference in a Random Coefficient Regression Model. *Econometrica*, *38*(2), 311. https://doi.org/10.2307/1913012

Tatoğlu, F.Y. (2020). Panel Zaman Serileri Analizi-Stata Uygulamalı, 3. Baskı, Beta Yayınevi: İstanbul, Türkiye

Torras, M., & Boyce, J. K. (1998). Income, inequality, and pollution: A reassessment of the environmental Kuznets curve. *Ecological Economics*, *25*(2), 147–160. https://doi.org/10.1016/S0921-8009(97)00177-8

Tugcu, C. T. (2018). Panel Data Analysis in the Energy-Growth Nexus (EGN). In *The Economics and Econometrics of the Energy-Growth Nexus*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-812746-9.00008-0

Uddin, M. M., Mishra, V., & Smyth, R. (2020). Income inequality and CO2 emissions in the G7, 1870–2014: Evidence from non-parametric modelling. *Energy Economics*, *88*, 104780. https://doi.org/10.1016/j.eneco.2020.104780

Ulucak, R., Danish, & Khan, S. U. D. (2020). Does information and communication technology affect CO2 mitigation under the pathway of sustainable development during the mode of globalization? *Sustainable Development*, *28*(4), 857–867. https://doi.org/10.1002/sd.2041

Ulucak, R., Yücel, A. G., & Koçak, E. (2019). The Process of Sustainability. In *Environmental Kuznets Curve (EKC)* (pp. 37–53). Elsevier. https://doi.org/10.1016/b978-0-12-816797-7.00005-9

United Nations. (2020). *World Social Report 2020 Inequality in a Rapidly Changing World*. https://doi.org/10.18356/7f5d0efc-en

Uzar, U., & Eyuboglu, K. (2019). The nexus between income inequality and CO2 emissions in Turkey. *Journal of Cleaner Production*, *227*, 149–157. https://doi.org/10.1016/j.jclepro.2019.04.169

WDI. (2020). *World development indicators*. World Bank, World Development Indicators.

Westerlund, J. (2007a). Estimating cointegrated panels with common factors and the forward rate unbiasedness hypothesis. *Journal of Financial Econometrics*, *5*(3), 491–522. https://doi.org/10.1093/jjfinec/nbm006

Westerlund, J. (2007b). Testing for error correction in panel data. *Oxford Bulletin of Economics*

and Statistics, *69*(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Wolde-Rufael, Y., & Idowu, S. (2017). Income distribution and CO2 emission: A comparative analysis for China and India. *Renewable and Sustainable Energy Reviews*, *74*(November 2016), 1336–1345. https://doi.org/10.1016/j.rser.2016.11.149

Xu, B., & Lin, B. (2015). Carbon dioxide emissions reduction in China's transport sector: A dynamic VAR (vector autoregression) approach. *Energy*, *83*, 486–495. https://doi.org/10.1016/j.energy.2015.02.052

Yang, B., Ali, M., Hashmi, S. H., & Shabir, M. (2020). Income Inequality and CO2 Emissions in Developing Countries: The Moderating Role of Financial Instability. *Sustainability (Switzerland)*, *12*(17). https://doi.org/10.3390/SU12176810

You, W., Li, Y., Guo, P., & Guo, Y. (2020). Income inequality and CO2 emissions in belt and road initiative countries: the role of democracy. *Environmental Science and Pollution Research*, *27*(6), 6278–6299. https://doi.org/10.1007/s11356-019-07242-z

You, W., & Lv, Z. (2018). Spillover effects of economic globalization on CO2 emissions: A spatial panel approach. *Energy Economics*, *73*, 248–257. https://doi.org/10.1016/j.eneco.2018.05.016

Zhang, C., & Zhao, W. (2014). Panel estimation for income inequality and CO2 emissions: A regional analysis in China. *Applied Energy*, *136*, 382–392. https://doi.org/10.1016/j.apenergy.2014.09.048

Zhu, H., Xia, H., Guo, Y., & Peng, C. (2018). The heterogeneous effects of urbanization and income inequality on CO2 emissions in BRICS economies: evidence from panel quantile regression. *Environmental Science and Pollution Research*, *25*(17), 17176–17193. https://doi.org/10.1007/s11356-018-1900-y