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Francesco Nicolli, Marianna Gilli, Francesco Vona

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By **Francesco Nicolli** (Department of Economics and Management, University of Ferrara)
Marianna Gilli (Department of Economics and Management, University of Ferrara)
Francesco Vona (University of Milan, Fondazione Eni Enrico Mattei and OFCE, Sciences Po)

Summary

This paper re-examines the relationship between per capita income, inequality, and per capita emissions while accounting for nonhomotheticity in green preferences and nonlinearities in the impact of economic growth on GHG emissions. Theoretically, our research is motivated by the fact that if environmental quality is a need with low priority on the hierarchical scale, the effect of inequality on emissions should vary depending on the level of income per capita. Specifically, for a given level of income per capita, a richer median voter will be more likely to approve of more stringent environmental policies, and thus, lower inequality is beneficial for the environment. With nonhomothetic preferences, the beneficial environmental effect of reducing inequality emerges only for countries that are sufficiently rich. We test this hypothesis by augmenting a standard EKC equation with the interaction between income per capita and the Gini coefficient. Our results for CO_2, SO_2 and N_2O emissions corroborate our main hypothesis: reducing inequality is beneficial for the environment only for rich countries.

Keywords: Inequality, Climate Change, GHG Emissions, Environmental Kuznets Curve, Sustainable Development Goals, Political Economy

JEL Classification: Q53, Q56, O15

Address for correspondence:
Francesco Vona
Program Director, Labour in the Low Carbon Transition (LILT)
Fondazione Eni Enrico Mattei (FEEM)
Corso Magenta 63, 20123 - Milan, Italy
e-mail: francesco.vona@unimi.it

Inequality and Climate Change: Two Problems, One Solution?*

Francesco Nicolli†, Marianna Gilli‡, Francesco Vona§**††

Abstract

This paper re-examines the relationship between per capita income, inequality, and per capita emissions while accounting for nonhomotheticity in green preferences and nonlinearities in the impact of economic growth on GHG emissions. Theoretically, our research is motivated by the fact that if environmental quality is a need with low priority on the hierarchical scale, the effect of inequality on emissions should vary depending on the level of income per capita. Specifically, for a given level of income per capita, a richer median voter will be more likely to approve of more stringent environmental policies, and thus, lower inequality is beneficial for the environment. With nonhomothetic preferences, the beneficial environmental effect of reducing inequality emerges only for countries that are sufficiently rich. We test this hypothesis by augmenting a standard EKC equation with the interaction between income per capita and the Gini coefficient. Our results for CO_2, SO_2 and N_2O emissions corroborate our main hypothesis: reducing inequality is beneficial for the environment only for rich countries.

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† Department of Economics and Management, University of Ferrara, Italy. Email: francesco.nicolli@unife.it
‡ Department of Economics and Management, University of Ferrara, Italy. Email: marianna.gilli@unife.it
§ Department of Environmental Science and Policy (ESP), University of Milan, Italy; Fondazione Eni Enrico Mattei (FEEM), Italy, Email: francesco.vona@unimi.it
** Fondazione Eni Enrico Mattei (FEEM), Italy.
†† OFCE Sciences-Po, France.

1. Introduction

Economic growth, inequality reduction and environmental preservation are three of the main pillars of the Sustainable Development Goals (SDGs), an ambitious and transformative agenda launched in 2016 by the United Nations to address the major challenges of our societies. The SDGs set several targets on different environmental issues (climate change, clean water, biodiversity and sustainable consumption) and put a strong emphasis on goals such as eradication of poverty, hunger reduction and economic and political inclusion. Despite the wide political consensus on the importance of reconciling environmental preservation and economic growth and, at the same time, mitigating inequality, there is no clear understanding of possible trade-offs or win–win approaches to achieving these goals, particularly with respect to economic inequality and environmental preservation.

This paper contributes to improving our understanding of these issues by looking at the relationship between GHG emission reductions (and thus climate change) and income inequality at the macro level. The main hypothesis that motivates our research is that environmental quality is (or may be perceived) as a "luxury good" in our increasingly unequal and polarized societies. Empirically, this leads to a straightforward modification of the empirical specification commonly used to study the relationship between growth, inequality and the environment, where the inclusion of the interaction between income per capita and inequality is essential. Using a very long (1960–2013) and comprehensive panel of countries (approximately 158 in the estimation sample) for three main pollutants (CO_2, SO_2, N_2O), the aforementioned modified empirical specification allows us to highlight a new and neglected facet of this relationship: namely, that reducing inequality may be extremely beneficial for curbing emissions and may thus mitigate climate change, but only for rich countries. This finding corroborates the widespread political concern that the increasing polarization of societies represents a key obstacle to achieving political support for ambitious climate policies in developed countries.

The starting point of our research is the inverted-U shape relationship between economic growth and emissions, which has been intensively scrutinized by the voluminous empirical literature on the environmental Kuznets curve (EKC) (Grossman and Krueger, 1991, 1995; Carson, 2009). At the onset of a country's economic growth trajectory, the shift from an agriculture-based to an industry-based economy increases environmental damage. After a certain income threshold is reached, however, economic growth becomes cleaner as the emergence of demand for environmental quality causes emissions to decrease or at least stabilize (e.g., Shafik and Bandyopadhyay, 1992; Panayotou, 1997; List and Gallet, 1999). However, recent empirical tests have found scant support for such a U-shaped relationship, especially in regard to CO_2 emissions (Stern, 2017, 2004; Kaika and Zervas, 2013).

Subsequent works have extended this research strand to further account for the role of income inequality. Theoretically, two contrasting mechanisms make the predicted effect of inequality unclear (for a survey, see Berthe and Elie, 2015). According to a political economy argument, lowering inequality may have a beneficial impact on the environment because for a given level of income per capita, a more equal society implies a richer median voter and thus—if environmental quality is a normal good—more support for stringent environmental policies (Torras and Boyce, 1998; Magnani 2000). On the other hand, because individuals shift to consumption of cleaner goods, the emissions embodied in a unit of consumption decrease with income. Thus, the mere aggregation of individual preferences implies that higher income inequality should have a positive impact on the environment (this is known as the aggregation argument; see Scruggs, 1998; Heerink et al., 2001). As the two effects tend to offset each other, it is not surprising that the empirical literature has not reached a firm conclusion on the relationship between inequality and emissions (Torras and Boyce, 1998; Ravallion et al., 2000; Heerink et al., 2001; Hubler, 2017; Grunewald et al., 2017).

In this paper, we show that the main reason for these inconclusive results rests upon a failure of previous empirical analyses to account for the possibility that environmental quality has low priority in the hierarchy of needs. Our modified specification adds the interaction between inequality and income per capita to a standard specification in which an indicator of environmental pressure is regressed against an index of inequality, a third-order polynomial in income and country and year fixed effects. Note that the EKC hypothesis requires that green preferences emerge above a certain income threshold and thus relaxes the homotheticity assumption used in the standard Solow–Ramsey growth model. Practically, this implies that aggregated statistical proxies of a country's preferences for emission reduction (expressed through either voting or consumption) depend on the first and higher moments of the income distribution as well as their interactions.

The theoretical mechanism behind this modified empirical specification is described in detail in the endogenous growth model of Vona and Patriarca (2011). To understand it, assume for simplicity that environmental quality is a good whose demand appears only after basic needs are satisfied—that is, above a certain income threshold. The aggregation of individual preferences implies that the share of individuals with positive demand for environmental quality differs depending on the level of average income per capita. In rich economies, where average income per capita is high and thus a large share of the population is potentially above the threshold, the more unequal the distribution of income, the higher is the share of individuals with income under the threshold. Redistribution would have, in this case, a positive impact on the demand for environmental protection, especially through the probability of voting for environmentally friendly legislation (reflecting the prediction of the political economy argument). In poorer countries, where average income per capita is low and thus a small share of the population is potentially above the threshold, higher income dispersion enables a few rich individuals to pass the threshold and thus increases the demand for environmental protection. Overall, the effect of inequality on the demand for environmental quality depends on the interaction between income per capita (the potential demand for a better environment) and inequality (the share of the potential demand that translates into effective demand).

By including this interaction, our empirical specification allows us to reveal a new and clear pattern in the relation between growth, inequality and emissions for both local (SO_2) and global (N_2O and CO_2) pollutants. More specifically, we find that the marginal effect of an increase in inequality on emissions levels is negative (i.e., it reduces emissions) in low-income countries but reverses and becomes positive for high-income countries (i.e., it increases emissions). When we exploit the full sample, the results are statically significant only in the case of SO_2 and N_2O emissions. However, in line with our theoretical explanation discussed above, when we restrict the analysis to a subsample of rich OECD countries only, an increase in inequality is associated with a significant increase in per capita emissions. Our finding indicates that the political economy argument prevails over the aggregation argument because greener goods are lower in the hierarchy of needs. This conclusion is reinforced by an additional empirical exercise where we show that lower inequality is associated with growing demand for environmental policies in OECD countries.

Our paper contributes to the literature on the inequality–environment nexus in four ways. First and foremost, our modified empirical specification allows us to reveal a new pattern in the relationship between inequality, growth and the environment. Indeed, the inconclusiveness of the evidence in previous works is due to their use of an empirical model that does not account for the fact that the effect of inequality on emissions depends on the level of income per capita (see the next section). Importantly, the model with the interaction term not only is theoretically sound but also is selected by standard statistical tests of specification (see Section 3 and Appendix B).

Second, our contribution uncovers the need to go beyond the representative agent framework used in integrated assessment models (Nordhaus, 2014; Golosov et al., 2014; Gillingham et al., 2018), political economy models (Fredriksson, 1997; Aidt, 1998) and endogenous growth models (Romer 1990; Peretto, 1998). Our empirical results suggest that to understand aggregated preferences for green policies, both the first and the second moment of the income distribution matter. A promising avenue to explore is full-fledged climate models with nonhomothetic preferences *à la* Bertola et al. (2006).

Third, our result implies that reducing inequality is of paramount importance for rich countries to meet the target of the SDGs or to strengthen the nationally determined contributions as defined by the Paris Agreement. This issue is even more relevant if we consider that the Gini index, our favoured measure of inequality, has been increasing significantly over the last 30 years,[1] making inequality one of the major constraints on decarbonisation.

Finally, we indirectly contribute to the environmental justice literature using micro data (Mohai et al., 2009; Banzhaf and Spencer, 2012; Boyce et al., 2016). One of the main findings of this literature and of the literature at the intersection of environmental and development economics (Greenstone and Jack, 2015) is that the willingness to pay for improvement in environmental quality increases with income. Using a similar assumption about individual preferences, we highlight an important political economy channel through which environmental injustice might emerge. Segregation amplifies the preference divide between the rich and the poor on local public goods such as pollution because it reduces the income of the median voter and thus her willingness to pay for a clean environment (see also Drupp et al., 2018). We show that this mechanism is also at work at the macro level, reaching a similar conclusion to that of Banzhaf et al. (2019), i.e., that reducing inequality is essential to increasing the willingness to pay for a clean environment.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical arguments upon which our empirical framework is built and reviews the related literature. Section 3 discusses the empirical strategy and presents the data together with stylized facts of the growth–inequality–environment relation. Section 4 presents the baseline results and then focus on rich countries, and Section 5 presents additional empirical exercises to evaluate the robustness of our results. Finally, Section 6 concludes.

2. Conceptual framework and related literature

The academic literature identifies two contrasting channels through which income inequality affects the environment: via *aggregation* of preferences and via the forces of *political economy*.

The *aggregation argument* posits that the impact of a reduction in inequality on the environment depends on the shape of the household income–emissions relationship. If households' contribution to

[1] In our OECD sample, the average Gini index increased from a value of approximately 0.26 in 1980 to a value of approximately 0.32 in 2015, reversing the previous trend of decreasing inequality registered in the 1960s and 1970s. In the UK and US, the increase was even more evident (21.35% and 15.29%, respectively), while in other countries such as Spain, the increase was 2 or 3 times lower (+7.18% in 2014 with respect to 1980). In northern EU countries, the variation was smaller: the Netherlands, for example, showed an increase of approximately 4%. In the full sample, the average increase between 1980 and 2014 was 8.4%.

a country's emissions is concave in household income, redistribution is expected to increase the level of pollution because income is shifted from households with a low marginal propensity to emit to households with a high marginal propensity to emit. In contrast, if households' emission impacts are convex in household income, then redistribution should have a positive effect on the environment (Heerink and Folmer, 1994; Scruggs, 1998; Heerink et al. 2001).

The *political economy argument* postulates that voting is the main channel through which environmental preferences are expressed and aggregated. Environmental quality is seen as a public good whose demand depends on the preference of the median voter. Consequently, for a given level of per capita income, a poorer median voter—and thus higher inequality—implies less weight on environmental quality relative to that on the private good. This translates into lower approval for ambitious environmental policies than in a country with a similar level of income per capita but lower inequality (Torras and Boyce, 1998; Magnani, 2000; Pfaff et al., 2004).

Although they start from opposite hypotheses, both arguments justify the inclusion of income inequality in the standard EKC framework used to estimate the relationship between economic growth and the environment.

Due to data limitations, early studies either explore the cross-sectional relationship between inequality and various measures of environmental quality without including country fixed effects (Scruggs, 1998; Heerink and Folmer, 1994; Torras and Boyce, 1998; Heerink et al. 2001) or exploit short panels with only a limited number of rich countries (Magnani, 2000). As anticipated in Section 1, their results are generally mixed, reflecting the authors' discretion in the choice of empirical specification and focus on different time spans, pollutants and proxies of environmental degradation.[2] For instance, the empirical analyses of Torras and Boyce (1998) and Magnani (2000) lend support to the political economy argument, indicating that a more equitable distribution of income results in better environmental quality or in the approval of more ambitious environmental policies.[3] In contrast, Scruggs (1998) and Heerink et al. (2001) find only weak evidence in support of the aggregation channel in cross-country regressions, while the microeconomic literature finds more convincing evidence of a concave-shaped relationship between income and environmental impacts.[4]

[2] Torras and Boyce (1994) and Scruggs (1998) use a set of local air and water pollutants; Heerink (2001) combines different indices of environmental degradation ranging from air pollution to deforestation and water quality and Magnani (2000) uses data on public R&D expenditure for environmental protection.

[3] This result is also confirmed by the more recent single-country case studies of Baek and Gweisah (2013) – for the US – and Kasuga and Takaya (2017) – for Japan.

[4] Evidence of concave preferences for the environment are found by Liu et al. (2013) and Büchs and Schnepf (2013) for energy consumption in China and the United Kingdom, respectively. In contrast, Cox et al. (2012) finds that rich households, on average, own bigger and newer cars, but are not interested in owning less polluting vehicles. More recently, Levinson and O'Brien (2019) study environmental Engel curves at the household level by exploiting a rich dataset on US consumer expenditure and on national pollution and find that the elasticity of pollution to income is smaller than one so pollution is a necessity.

An additional criticism of the early literature is that it fails to consider income as a mediating factor in the relationship between inequality and the environment and consequently cannot reconcile the contrasting effects of the *aggregation* and *political economy* channels. Using a theoretical framework where demand is a driver of economic growth (Murphy et al., 1989; Bertola et al., 2006), Vona and Patriarca (2011) build a model that contributes to rationalizing these inconclusive results. Key to their model is the introduction of a hierarchy between a "luxury" green good and a "necessity" nongreen good. Because consumption of the green good begins only after a certain income threshold is reached, the effect of inequality on the adoption of the green product is highly nonlinear. Indeed, for rich countries, where the median consumer (or voter) is rich enough to afford the green good (or vote for stringent climate policies), reducing inequality is beneficial for the environment, while in poor countries, an increase in inequality allows a few rich consumers to buy the green good.[5] The key mechanism is that aggregation of preferences depends on the share of consumers (or voters) who are above the thresholds. This share decreases (increases) with inequality if average income is high (low). To see this, imagine a society with an average income below the threshold. In such a society, increasing inequality allows some consumers to afford consumption of the green good. In turn, if average income is above the threshold, everybody can afford the green good in a perfectly equal society, but increased inequality excludes some groups from consuming it. Overall, the model of Vona and Patriarca (2011) provides theoretical support for our empirical specification, where we augment the standard EKC model with inequality and its interaction with income per capita.

A few contributions, closely related to ours, account for the possible nonlinear effect of inequality on emissions by interacting the Gini coefficient with GDP per capita. Ravallion et al. (2000) are the first to account for the interplay between inequality and income and find that the income elasticity of carbon emissions is an increasing function of the Gini index while higher inequality exerts a negative and significant direct impact on emission levels. However, their empirical framework is limited by the low quality of the Gini data, which, at the time of their study, were not strictly comparable across countries and had several missing values, forcing the authors to use a time-invariant measure of inequality. Grunewald et al. (2017) use the time-varying Gini coefficient in the interaction and a group fixed effects estimator (Bonhomme and Manresa, 2015). Similarly, they find that at a low level of GDP per capita, there is a negative relationship between income inequality and per capita carbon emissions, while in high-income countries, reductions in income inequality cause emissions to decrease. Finally, Hubler (2017) indirectly accounts for the heterogeneous effect of inequality across emission levels by using conditional quantile regressions. He finds that higher inequality reduces per

[5] Notably, this result holds under fairly general conditions even if there are learning-by-using spillovers from the rich to the poor in the consumption of green goods.

capita CO_2 emissions and that the effect is larger in the highest percentiles of the CO_2 distribution. We argue that a quantile-regression framework is not the best available tool to address our research question. Indeed, conditional quantile regression techniques estimate the effect of inequality (and GDP per capita) along the residualized distribution of emissions, while our theoretical framework predicts that the effect varies depending on GDP per capita. Moreover, there is no clear way to control for time-invariant unobserved heterogeneity in conditional quantile regressions (Koenker and Hallock, 2001).

Our study extends the literature in three ways. First and foremost, we find a clear and robust pattern in the effect of inequality on the environment, while the results presented in recent works are highly sensitive to the inclusion of country fixed effects to control for time-invariant unobserved heterogeneity.[6] This is a crucial point for the credibility of our empirical framework: the inclusion of fixed effects allows us to control for time-invariant institutional, geographical and cultural factors that have a large influence on the country's propensity to reduce emissions. Unlike previous authors, we use the theoretical model of Vona and Patriarca (2011) to provide theoretical foundations for the inclusion of inequality and its interaction with income per capita within a standard EKC framework.

Second, we provide substantial evidence of the importance of the political economy channel by focusing on rich countries only and on the determinants of environmental policy stringency. We show that as theoretically expected, the political economy channel drives the negative conditional correlation between inequality and emissions for rich countries.

Finally, we enrich the recent literature on inequality and emissions—which generally focuses on per capita CO_2 emissions only—by considering more pollutants, a longer time span and a larger sample of countries. In particular, the inclusion of a wider set of pollutants, both local and global, allows us to have a broader view of the inequality-environment nexus and helps us to reconcile our results with the literature. As we know from the EKC debate (Lopez, 1994; Stern, 2017, 2004), local pollutants (e.g., SO_2) exhibit the expected inverted-U shaped relationship with income, but the same cannot be said for global pollutants, such as carbon dioxide (CO_2), due to possible free-riding behaviour in contributions to emission reductions (Carson, 2009). The same argument applies in our case: when we consider the *political economy mechanism*, we expect the effect of inequality to be stronger for local pollutants. Indeed, reductions in local pollutants have more direct benefits on the population in terms of improved health, while reductions in global pollutants have only cobenefits. Moreover, regional and national authorities are more likely to enact policies to correct local

[6] The results in Grunewald et al. (2017) and Hubler (2017), for instance, are statistically significant only when authors employ their preferred estimator (respectively, a group fixed effect model and a quintile regression) but become insignificant once they include country fixed effects.

environmental externalities—the success of which depends only on their effort—than global ones—whose success often depends on a large host of factors beyond the control of local governments (e.g., international agreements, intercountry negotiations and the overall commitment of other governments).

3. Empirical framework

This section presents our empirical strategy and the data. More specifically, Section 3.1 introduces the data and some preliminary statistics, Section 3.2 discusses our estimating equation, and Section 3.3 discusses key extensions.

3.1 Data

The data sources used in this paper are quite standard. We consider three different types of air pollutants as dependent variables: two global pollutants, i.e., carbon dioxide emissions (CO_2) and nitrous oxide emissions (N_2O), and a local pollutant, i.e., sulfur dioxide emissions (SO_2). These three pollutants cover 82% of world greenhouse gas emissions (IPCC, 2014).[7]

Gross domestic product and population data are retrieved from the Penn World Tables (Feenstra, Inklaar, and Timmer 2015). For inequality data, the gap between median and average income would be the ideal statistic to account for the aggregation effects described in, e.g., Magnani (2000) and Vona and Patriarca (2011). However, because data on median incomes are available for OECD countries only, we rely on a second-best measure of inequality, i.e., the Gini coefficient. We use the net Gini coefficient (after taxes and transfers) because the level of inequality can differ substantially after redistributive taxation.

Data on inequality are from the Standardized World Income Inequality Database (SWIID; Solt, 2016), which has the advantage over other well-established sources such as the "All the Ginis" database from the World Bank of offering the highest geographic and temporal coverage and is generally considered to be highly reliable (Atkinson and Brandolini 2001, 2009). To corroborate our results, in the empirical analysis, we test the robustness of this choice by using World Bank data (see Table C.2 in Appendix C).

Table 1 presents all summary statistics of our main variables. As shown, the number of observations and the year availability differ according to the variable considered. For example, while CO_2 and N_2O emissions are available for years until 2012, SO_2 was collected only until 2005. Similarly, data for N_2O are not available for years before 1970, while the CO_2 and SO_2 series start in 1960. Their country coverage also differs: the CO_2 and N_2O emissions samples cover 170 countries,

[7] The other main GHGs are methane (16%) and fluorinated gases (2%).

while the SO_2 sample covers only 119. Among the independent variables, the lowest country coverage is generally found for the Gini indicators, with SWIID containing 153 countries and “All the Ginis” 133. This restricts the observations available for our estimation: the CO_2 model is based on a sample of 4218 observations (158 countries), the SO_2 model on 3021 (119 countries) and the N_2O model on 3964 (159 countries).[8] The last two columns of the table allow us to observe the long-term growth of the variables of interest. We note, for example, the well-known increase in inequality, especially from the 1980s, as well as an increase in both GDP per capita and CO_2 emissions. Conversely, both SO_2 and N_2O decreased during the period of observation.

[8] The available data present several missing values, which proportion depend on the variable and country considered. We imputed the moving average of the two adjacent years to fill internal missing observation, but we never extended a time series before (resp. after) the first (resp. last) available year. See the Appendix A for details.

Table 1 – Descriptive statistics of the variables used in the baseline model

Variable	Description & unit of measure	Source	Obs.	Year availability	Countries availability	Mean	Std. dev	Min	Max	1980–2014 variation (2005 for SO_2 ;2012 for N_2O)	1990–2014 variation (2005 for SO_2 ;2012 for N_2O)
CO_2	CO_2 emissions in tons per capita	Oak Ridge National Laboratory (USA)	6,679	54	141	3.74	4.84	0.00	41.04	0.51	0.66
SO_2	SO_2 emissions in thousand tons per capita	NASA (USA)	3,040	45	115	0.03	0.04	0.00	0.35	-0.03	-0.02
N_2O	N_2O emissions in tons per capita	World Bank	5,641	42	142	0.80	1.56	0.00	41.10	-0.34	-0.18
Ineq	Gini coefficient (net)	Standardized World Income Inequality Database (SWIID)	4,681	54	144	0.37	0.09	0.14	0.67	-0.03	-0.01
GDPpc	Gross domestic product per capita in purchasing power parity (ppp)	Penn World Tables (9.0)	7,050	54	144	9,900	11,400	400	95,200	966.05	796.58
$\Delta\ln(Pop)$	Yearly variation of log population	Penn World Tables (9.0)	6,979	54	144	0.02	0.01	-0.20	0.13	-0.01	-0.02

Note: Country data availability differs by year. We refer to the maximum number of countries available. The countries included in the analysis are Angola, Albania, Algeria, Argentina, Armenia°, Australia, Austria, Azerbaijan°, Burundi, Belgium, Burkina Faso, Bangladesh, Bulgaria, Bahrain, Bosnia and Herzegovina°, Belarus°, Belize, Bolivia, Brazil, Barbados, Bhutan, Botswana, Central African Republic, Cambodia, Canada, Switzerland, Chile, China, Côte d'Ivoire, Cameroon, Colombia, Cape Verde, Costa Rica, Croatia, Cyprus, Czech Republic°, Germany, Djibouti, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia°, Ethiopia, Finland, Fiji, France, Gabon, Georgia°, Germany*, Ghana, Guinea, Gambia, Guinea-Bissau, Greece, Guatemala, Guyana, Hong Kong, Honduras, Haiti, Hungary, Indonesia, India, Ireland, Iran, Iceland, Israel, Italy, Jamaica, Jordan, Japan, Kazakhstan°, Kenya, Kyrgyzstan°, South Korea, Lao, Lebanon, Saint Lucia, Sri Lanka, Lesotho, Lithuania, Luxembourg, Latvia°, Morocco, Moldova°, Madagascar, Maldives, Mexico, Macedonia°, Mali, Malta, Montenegro, Mongolia, Mozambique, Mauritania, Mauritius, Malawi, Malaysia, Namibia, Niger, Nigeria, Nicaragua, Netherlands, Norway, Nepal, New Zealand, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Paraguay, Puerto Rico, Papua New Guinea, Romania, Russia°, Rwanda, Serbia, Senegal, Singapore, Sierra Leone, Slovakia°, Slovenia, Spain, South Africa, Sweden, Swaziland, Seychelles, Syrian Arab Republic, Thailand, Tajikistan°, Turkmenistan°, Trinidad and Tobago, Tunisia, Turkey, Tanzania, Taiwan, Uganda, Ukraine, Uruguay, United Kingdom, United States, Uzbekistan°, Venezuela, Vietnam, Yemen*, Zambia, and Zimbabwe. *These are countries in which emissions have been added together. °These are countries in which CO2 emissions have been split.

The last two columns of the table report the absolute variation in all variables between 1980 and 2014 and 1990 and 2014. Both show that the variation in our sample is higher for the interval starting in 1990 than for the interval starting in 1980. We note that the SO_2 data are available only for years until 2005; thus, for this pollutant, the absolute variations are computed for different time ranges: 1980 to 2005 and 1990 to 2005. Similarly, the N_2O data are available only for years until 2012; thus, the variations are computed for the time spans 1980 to 2012 and 1990 to 2012.

3.2 Econometric Specification

The main idea of this paper is to modify the standard empirical model used to estimate the relationship between inequality, growth and emissions to account for the fact that environmental quality is lower in the hierarchy of needs. Our favoured specification is the following augmented environmental Kuznets curve:

$$\begin{aligned} ln(e_{it}) = \beta_1 GDPpc_{it} + \beta_2 (GDPpc_{it})^2 + \beta_3 (GDPpc_{it})^3 + \beta_4 Ineq_{it} \\ + \beta_5 (GDPpc_{it} \times Ineq_{it}) + \beta_6 \, \Delta ln(Pop_{it}) + \mu_i + \mu_t + \varepsilon_{it} , \end{aligned} \tag{1}$$

where $\varepsilon_{it}$is the error term; μ_i are country fixed effects that absorb time-invariant unobservable country characteristics, such as geography, culture and institutions; and μ_t are time dummies capturing common shocks to all countries in a given year, such as global recessions or oil price shocks.[15] The growth rate of the population $\Delta \log(Pop_{it})$ is included to capture the demographic transition, namely, compositional changes in the population age induced by economic development, which has been shown to have a significant effect on GHG emissions (Galeotti et al., 2011; Casey and Galor, 2017). Other controls, such as trade and institutional quality, capture mechanisms explaining the relationship between inequality and emissions and thus are included in a further extension (see the next section).

The dependent variable is the log of per capita emissions (e_{it}) of one of the three GHGs considered (CO_2, SO_2 or N_2O) in country i at period t. In line with the literature on the EKC (e.g., Stern, 2004), we take the logarithm of the emissions variables for two reasons: first, it is a simple monotonic transformation that allows us to smooth the series, and second, we can interpret the coefficients as semielasticities. The main variables of interest are $Ineq_{it}$, measured with the Gini coefficient—our preferred measure of inequality—and the interaction of inequality with GDP per capita, $GDPpc_{it} \times Ineq_{it}$, which captures the nonhomotheticity of green preferences.

The influence of per capita GDP ($GDPpc_{it}$) is captured by a standard third-order polynomial as in most research papers (on this point, see the literature reviews by Dinda, 2004, and Kaika and Zervas, 2013). However, there are other functional forms that capture nonlinearity in the income–emission relationship, and the EKC literature has not reached a consensus on which is the best choice. List and Gallet (1999) and Lau et al. (2014), for instance, use a log–log quadratic specification, while Panayotou (1997) uses a cubic specification in levels. Our preference for a log-linear cubic specification rests on the fact that the cubic specification allows us to capture nonlinearity beyond the

[15] We estimate Model (1) by clustering standard errors at the country level, thus allowing for a general form of autocorrelation in the residuals.

inflection point of the EKC without imposing additional concavity through the log-transformation of GDP per capita. Indeed, a so-called N-shaped Kuznets curve can emerge because for high levels of GDP per capita, an increase in the scale of the economy may offset the effect of green technological change and of the transition to a service-based society—the two main factors behind the downwards-sloping part of the EKC (e.g., Shafik 1994).[16]

Importantly, our choice to model GDP as a third-degree polynomial function is also supported by standard measures of goodness of fit, which are discussed extensively in Appendix B. In Table 2, we compare three log-linear cubic models (Equations 1, 2 and 3, which are, respectively: our preferred specification, a traditional Kuznets model, and an EKC augmented with inequality), with a log-log quadratic specification (Equation 4) and a log-log cubic specification (Equation 5).[17] As shown there, all measures of goodness of fit are superior for the log-linear cubic model augmented with inequality and its interaction with GDP per capita (Equation 1), for SO_2 and N_2O (see Columns 2 and 3, respectively). In particular, the adjusted R squared is always higher for Equation 2, and the AIC and BIC are always lower. The same does not hold for CO_2 (see Column 1), where the quadratic model shows a better fit. We also decide to use the specification of Equation 1 for CO_2 for the sake of coherence. As will be clear in the results' section, CO_2 merits further analyses in section 4.2 to improve the interpretation of the results.

With a similar intent, we also provide some empirical evidence to justify the theoretically driven choice of the preferred model of Equation (1), which includes both inequality and its interaction with income. First, we present in Figure 1 the scatterplot of the log of per capita emissions for each available country–year combination (on the Y axis) by per capita GDP level (on the X axis) in three different terciles of the inequality distribution (low, medium and high levels of inequality). Although there is some heterogeneity across pollutants, a visual inspection of Figure 1 highlights that the downwards-sloping branch of the EKC pattern between income per capita and emissions is more evident in countries with low inequality.

Second, in Table 3, we perform a specification test to compare our favoured model, which includes inequality and its interaction with income (Equation 1), with a cubic EKC model (Equation 2), and a cubic EKC augmented with inequality only (Equation 3). The comparison of the three models allows us to understand *i.)* whether it is worth adding inequality in general and *ii.)* whether it is worth adding inequality interacted with GDP per capita. Because the three models are nested, we use a log-likelihood ratio specification (LR) test as in Ravaillon et al. (2000). The LR test compares

[16] With a few exceptions (e.g., Fosten et al., 2012), a log-log cubic specification is generally not considered in the literature, as the nonlinearity of per capita GDP is already taken into account through the inclusion of the cubic term, with no need for additional log transformations.
[17] The detailed results for these two models are reported in Tables 1 to 4 of Appendix B.

the fit of two nested models by juxtaposing their log-likelihoods: failure to reject the null hypothesis implies that the model with fewer variables (the nested model) is preferred. The clear advantage of the LR test over measures of goodness of fit is that it provides the best model with a precise level of statistical confidence.

Overall, when comparing Equations 1, 2 and 3, the LR tests presented in Table 3 always reject the null hypothesis that the nested model is preferred to the most comprehensive one, statistically supporting our choice to adopt Equation 1 as the benchmark specification in the main analysis. In other words, for all three pollutants, a specification that also includes inequality fits the data better than a standard EKC model (as shown by comparing Eq. 2 to Eq. 1), but the best fit is obtained when we also include the interaction between inequality and income per capita (as shown by the comparison of Eq. 3 to Eq. 1).[18]

Table 2 – Statistics for model selection

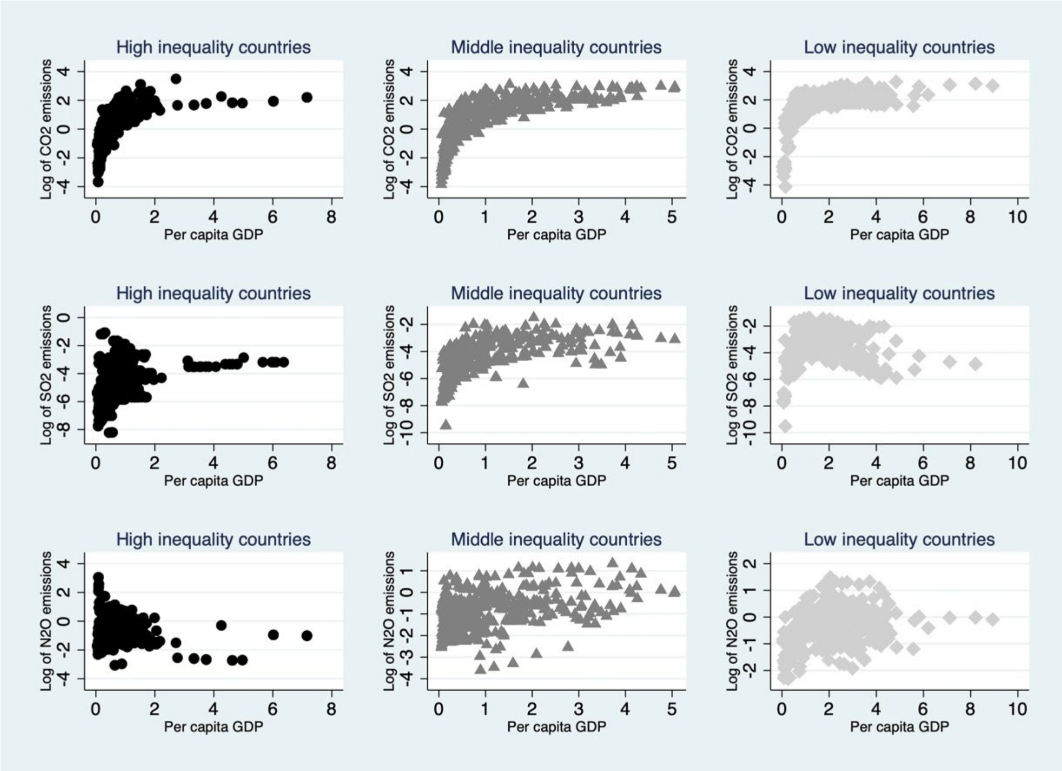
	Equation	**(1)** **CO_2**	**(2)** **SO_2**	**(3)** **N_2O**
	Log-Linear Models			
(1)	$Log(e_{it}) = \beta_1 GDPpc_{it} + \beta_2 (GDPpc_{it})^2 + \beta_3 (GDPpc_{it})^3 + \beta_4 Ineq_{it} + \beta_5 (GDPpc_{it} \times Ineq_{it}) + \beta_6 \Delta Pop_{it} + \mu_i + \mu_t + \varepsilon_{it}$	Adj. R^2: 0.42 AIC: 590.61 BIC: 970.82 Obs: 4171	Adj. R^2: 0.42 AIC: 3286.83 BIC: 3593.34 Obs: 3015	Adj. R^2: 0.21 AIC: -1066.55 BIC: -765.43 Obs: 3917
(2)	$Log(e_{it}) = \beta_1 GDPpc_{it} + \beta_2 (GDPpc_{it})^2 + \beta_3 (GDPpc_{it})^3 + \beta_4 \Delta Pop_{it} + \mu_i + \mu_t + \varepsilon_{it}$	Adj. R^2: 0.42 AIC: 621.94 BIC: 989.36 Obs: 4171	Adj. R^2: 0.29 AIC: 3915.58 BIC: 4210.14 Obs: 3015	Adj. R^2: 0.18 AIC: -943.22 BIC: -654.67 Obs: 3917
(3)	$Log(e_{it}) = \beta_1 GDPpc_{it} + \beta_2 (GDPpc_{it})^2 + \beta_3 (GDPpc_{it})^3 + \beta_4 Ineq_{it} + \beta_5 \Delta Pop_{it} + \mu_i + \mu_t + \varepsilon_{it}$	Adj. R^2: 0.41 AIC: 620.23 BIC: 994.15 Obs: 4171	Adj. R^2: 0.29 AIC: 3917.58 BIC: 4218.15 Obs: 3015	Adj. R^2: 0.17 AIC: -941.22 BIC: -646.44 Obs: 3917
	Log-Log Models			
(4)	$Log(e_{it}) = \beta_1 Log(GDPpc_{it}) + \beta_2 Log(GDPpc_{it})^2 + \beta_3 \Delta Pop_{it} + \mu_i + \mu_t + \varepsilon_{it}$	Adj. R^2: 0.49 AIC: -4.46 BIC: 356.76 Obs: 4171	Adj. R^2: 0.25 AIC: 4065.327 BIC: 4353.87 Obs: 3015	Adj. R^2: 0.19 AIC: -980.88 BIC: -698.53 Obs: 3917
(5)	$Log(e_{it}) = \beta_1 Log(GDPpc_{it}) + \beta_2 Log(GDPpc_{it})^2 + \beta_3 Log(GDPpc_{it})^3 + \beta_4 \Delta Pop_{it} + \mu_i + \mu_t + \varepsilon_{it}$	Adj. R^2: 0.51 AIC: -198.26 BIC: 169. 33 Obs: 4171	Adj. R^2:0.32 AIC: 3739.37 BIC: 4033.92 Obs: 3015	Adj. R^2: 0.18 AIC: -1003.54 BIC: -714. 96 Obs: 3917

Note: The column "Equation" reports the equations of the five specifications that we tested in our model selection process. The columns "CO_2", "SO_2" and "N_2O" report the statistics of each specification run with the three pollutants as dependent variables. Statistics include the adjusted R2 (*Adj. R2*), Akaike information criterion (*AIC*), Bayesian information criterion (*BIC*), and number of

[18] In the case of SO_2 and N_2O, this result is also confirmed by the adjusted R-squared, AIC and BIC results (Table 2). However, again, the same does not hold for CO_2, where Equation 1—despite being preferred over the other log-linear models—shows a lower fit than Equations 4 and 5.

observations in each regression (*Obs.*).

Figure 1 – Relation between polluting emissions and GDP per capita by inequality level



Note: The nine scatter plots are organized as follows: each row corresponds to a pollutant (CO_2, SO_2 and N_2O); each column corresponds to an inequality group. Specifically, the first one includes high-inequality countries, defined as all countries between the 66th and the 99th percentiles of the Gini coefficient distribution; the second one presents medium-inequality countries, including those between the 33rd and the 66th percentiles of the Gini distribution; and finally, the third column displays low-inequality counties, i.e., those falling between the 1st and the 33rd percentiles on the Gini. Per capita GDP is always in thousands of dollars of PPP.

Table 3 – Likelihood ratio test for model selection (p values in brackets)

LR test	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Eq. 3 *(EKC augmented with Ineq) vs.* Eq. 1 *(EKC augmented with Ineq and Ineq x GDP)*	31.57 (0.000)	632.82 (0.000)	127.31 (0.000)
Eq. *2 (Standard EKC) vs.* Eq. 1 *(EKC augmented with Ineq and Ineq x GDP)*	35.26 (0.000)	632.82 (0.000)	127.37 (0.000)

Note: *p-values* in brackets. The LR test compares the fit of two nested models by comparing their log-likelihoods under the null hypothesis that the restricted model fits the data as well as the unrestricted one.

3.3 Extensions

Next, we conduct a series of complementary analyses to understand the mechanisms through which inequality affects emissions. To address this point, we restrict the analysis to a smaller sample of rich and democratic OECD countries for which we can also observe reliable measures of environmental policy stringency. According to our conceptual framework, these countries are those in which reducing inequality should be beneficial for the environment, especially through the approval of stringent environmental policies, i.e., the political economy channel is expected to be prevalent.

First, we estimate a slightly modified version of Equation (1) by removing the interaction between inequality and income per capita for OECD countries only. The choice of a different specification is motivated by the fact that in the sample of OECD countries, income per capita levels are much more homogenous than in the larger sample and thus the inequality term already captures the effect on rich countries. As is evident in the results section, this choice is also supported by the results for the whole sample of countries: we observe that the slope of the inequality–emission relationship changes in rich countries. Second, to directly explore the political economy mechanism, we fit the same model without the interaction term, using as dependent variables seven different indices of environmental policy stringency (EPS) developed at the OECD (Botta and Kòzluk, 2014). We differentiate across different policy instruments (standards, taxes, subsidies, emission trading, etc.) because both political acceptability and the effect on emissions are likely to vary across instruments (Goulder and Parry, 2008). In this specification, including country fixed effects would leave us with too little data variation to obtain consistent estimates, as the EPS indices move slowly. We replace country fixed effects with the presample levels of three GHG emissions per capita, which proxy the component of green preferences unrelated to the levels of GDP per capita and inequality.

3.4 Robustness

In this section, we present several robustness tests based on the benchmark specification of Equation 1. In particular, we consider additional covariates that may capture time-varying characteristics correlated with both inequality and emissions (e.g., political institutions), alternative measures of inequality, and the possible effect of our choice to impute missing data.

As our first robustness exercise, we account for the concern raised by Grunewald et al. (2017) that unobserved heterogeneity is mainly time varying by running a model in which we control for country-specific time trends instead of including country fixed effects.

Second, we acknowledge that other important intervening factors, such as (time-varying) proxies of institutional quality and openness to trade, may capture part of the effect of inequality. Thus, we present a set of estimates that include other variables that may act as confounders in the relationship between inequality and emissions, such as incoming foreign direct investment (FDI), trade openness (Hubler, 2017) and democracy (Kashwan, 2017). FDI captures the effect of foreign-induced capital accumulation, one of the factors behind the EKC. Moreover, FDI may create technological spillovers that are likely to reduce emissions, as noted in Perkins and Neumayer (2012). International trade has a less clear effect: on the one hand, it can induce positive technology spillovers and increase productivity (Melitz, 2003); on the other hand, it can serve as a tool to displace a country's polluting emissions abroad (Cole, 2004). Finally, the effect of a richer median voter predicted by the political economy argument is more likely to emerge in majoritarian democracies, where the electorate can influence environmental policy formation. To control for the effect of different political regimes, we include in the estimates a factor variable that ranges from 1 (most autocratic) to 8 (most democratic). The democracy data are taken from the Polity IV Project, while the data for FDI and trade openness are retrieved from the World Development Indicator database of the World Bank. However, all these additional covariates are potentially endogenous, and for this reason, we include them only in this robustness exercise.

Finally, we conduct three additional robustness checks. First, we are aware that persistency in time series can become an issue in a long panel such as ours (see Stern 2010 and Wagner 2008), but due to the highly unbalanced nature of the dataset, which prevents us from conducting most panel stationarity tests (especially the so-called second-generation tests, strongly suggested in Wagner 2008), we address this issue by simply taking the five-year average of both the dependent and independent variables and run our main specification in Equation 1 with the transformed dataset. Second, we control for the sensitivity of the regression results to the measure of inequality adopted by substituting the Gini coefficient from the SWIID with the one from the "All the Ginis" database (Milanovic, 2013). Third, we check the sensitivity of our results to the process of interpolation adopted to deal with missing values. We control for this potential bias by augmenting Equation 1 with a set of dummy variables that correspond to each interpolated observation.

4. Results

4.1 Main estimation results

Table 4 displays the results of the model in Equation 1. Our dependent variables are CO_2 (Column 1), SO_2 (Column 2) and N_2O (Column 3). Note first that our results confirm that including the third-order polynomial in *GDP per capita* yields an N-shaped environmental Kuznets curve for all three pollutants (Panayotou 1997; Friedl and Getzner, 2003; Churchill et al., 2018). Conversely, population growth has no statistically significant effect on emissions, consistent with the recent work by Churchill et al. (2018) but in contrast to the results of Gerlagh et al. (2022) and Galeotti et al. (2011), which, however, are obtained using a different analytical framework and thus are not strictly comparable with ours.

Turning to our main results, for all pollutants, the *Ineq* coefficient and its interaction with *GDP per capita* show the signs predicted under the theoretical framework laid out in Section 2. First, the fact that the baseline effect of inequality is negative implies that higher inequality is associated with lower GHG emissions, at least among the poorest countries. Second, the coefficient of the interaction between the *Ineq* coefficient and *GDP per capita* is positive, implying that among rich countries, a more equal distribution of income may be associated with lower GHG emissions. This novel result in comparison to the findings in previous literature (see Berthe and Elie, 2015) lends support to our hypothesis that as environmental quality is a good with low priority in the hierarchy of needs, demand for it appears only above a certain income level after basic needs are satisfied. Indeed, the larger the share of consumers (or voters) above this income threshold is, the greater the demand for green goods and stringent climate policies. In rich countries (i.e., those with average income above the threshold), this share can be increased by reducing inequality, as everybody may potentially be above the threshold. In poor countries (i.e., those with average income below the threshold), the opposite occurs, and the share can be increased only by allowing to a few people to pass the threshold.

Next, it is important to determine the switching point where the effect of inequality changes sign and to detect whether, for some countries in our sample, this switch actually occurs. To this end, Figures 2, 3 and 4 provide a visual representation of the marginal effects of inequality estimated in Table 4 for each pollutant. For each of the three panels, the horizontal axis represents percentiles of the cross-country distribution of *GDP per capita*, while the bars report the marginal effects along with the 95% confidence intervals. These figures also reveal the difference in the slope of the relationship across pollutants.

In the case of CO_2 (Figure 2), the marginal effect of inequality grows with income per capita but always remains statistically insignificant. Inequality is only nearly significant at the 90th percentile of *GDP per capita* (p-value=0.15). We further dig into this inconclusive finding for CO_2 in the next section. Conversely, the marginal effects are estimated more precisely for the other two GHGs. An increase in inequality is associated with a reduction in SO_2 emissions until the 52nd percentile of the *GDP per capita* distribution and with an increase in emissions afterwards; the effect is significantly different from zero until the 38th percentile of *GDP per capita* and after the 61st percentile (Figure 2). The switching point in the effect of inequality for N_2O is the 49th percentile, but the effect is statistically significant at the conventional level only after the 71st percentile.

To quantify the results presented in Table 4, we calculate the effect of a drop in the Gini index from the value observed in the last year of our panel to its level in 1985, when inequalities were, on average, at the lowest level in our estimation sample.[19] For SO_2, such a hypothetical reduction in

[19] We quantify the result according to the following formula: $\Delta \ln(\bar{e})\bar{\text{l}} = \hat{\beta}_4(\overline{Ineq}_n - \overline{Ineq}_{1985}) + \big(\hat{\beta}_5(\overline{Ineq}_n - \overline{Ineq}_{1985}) \times \overline{GDPpc}_n\ \big)$, where n is the last available year for each type of emissions, i.e., 2014 for CO_2, 2005 for SO_2 and 2014 for N_2O. The formula allows us to obtain the absolute variation in year n, expressed in log points, had average inequality remained at the 1985 level. To obtain the values presented in the text, we transform the log points in levels by taking the $\exp(\Delta\overline{\overline{\ln(e)}})$ and calculate the percentage change by dividing the absolute variation by the level of emissions in year n.

inequality would be associated with an approximately 44% decrease in per capita emissions when income is at its median level and a 54% or 76% decrease when income is, respectively, at the 75th or 90th percentile. This effect is large, but we note that *Gini* increased from 0.328 in 1985 to 0.383 in 2005, which is similar to the difference in inequality between Canada and Syria in the last year of the dataset. The effect on N_2O is much smaller: a Gini at the mid-1980s level would imply a reduction of emissions by only 1.45% and 1.48% for countries with a level of income at the 50th and 75th percentiles, respectively, while the effect increases to 1.56% when GDP is at the 90th percentile. In the case of CO_2, where the effect of inequality became barely significant only at the 90th percentile of GDP per capita, a reduction in the Gini to its lowest level is associated with a 2.5% reduction in emissions.

The main takeaway from these results is that our modified specification allows us to reconcile the inconclusive results on the relationship between inequality and emissions found in previous studies (e.g., Grunewald et al. 2017; Hubler, 2017; Ravallion et al. 2000). From a global policy perspective, this result suggests that only rich countries with a sufficient level of socioeconomic cohesion will be willing to take the lead in international negotiations on climate change. The contrast between the steady commitment of EU countries, especially Nordic and central European countries, and the inconsistent commitment of the US obviously points in this direction. Overall, the rapidly increasing inequality (along with the associated political polarization) in all developed countries risks becoming a serious obstacle to ensuring internal political support for ambitious climate policies, both domestically and internationally.

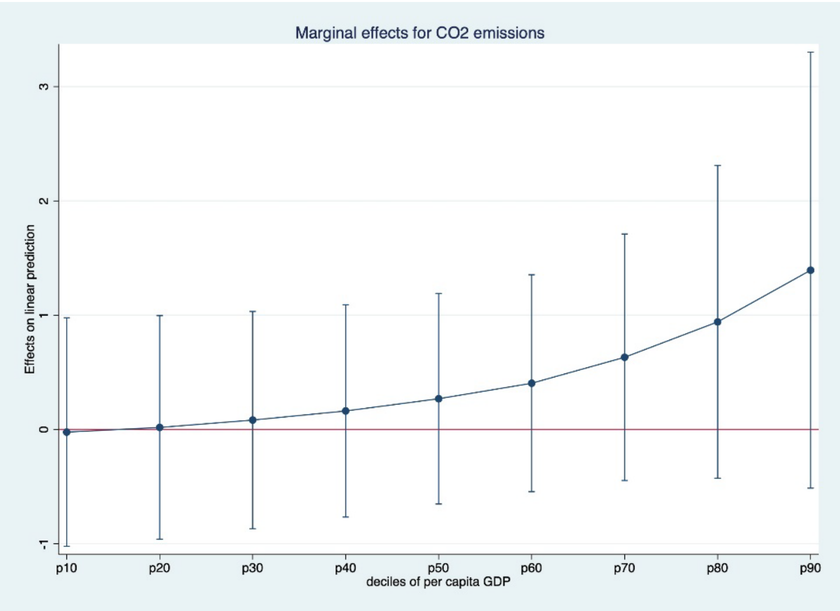
Our results also highlight notable differences across pollutants that seem consistent with the political economy explanation of the inequality–emissions relationship. When emissions have stronger local cobenefits, i.e., on health, as in the case of SO_2, the preferences of the median voter are more likely to be translated into ambitious environmental policies. Indeed, health benefits are detectable and mostly depend on domestic environmental policies. In contrast, for purely global GHGs such as CO_2, the success of the policy also depends on other countries' efforts; thus, local environmental preferences are less likely to translate into direct policy support, as citizens may internalize the fact that their choices have little effect globally. The history of environmental regulation resonates with this interpretation. While regulations for the reduction of SO_2 emissions have a long historical record (in the US, for instance, sulfur dioxide quality standards were introduced at the beginning of the 1970s with the Clean Air Act), policies to curb CO_2 emissions took much longer to take off, and their stringency is very substantially far from that suggested by climate models (Nordhaus, 2018; Kalkuhl et al., 2020). The next part of the paper provides further empirical analyses to provide some evidence for the political economy explanation of the inequality–emissions relationship.

Table 4 – Inequality-augmented EKC models for three main pollutants: Carbon dioxide (CO_2), sulfur dioxide (SO_2) and nitrogen oxide (N_2O)

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
GDP per capita	0.897***	-0.407	0.171
	(0.214)	(0.352)	(0.163)
GDP per capita (squared)	-0.282***	-0.513***	-0.113***
	(0.047)	(0.101)	(0.029)
GDP per capita (cube)	0.021***	0.045***	0.008***
	(0.003)	(0.009)	(0.002)
Ineq	-0.084	-3.854***	-0.619
	(0.530)	(0.952)	(0.458)
Ineq x GDP per capita	0.465	4.788***	0.848***
	(0.345)	(0.561)	(0.260)
Population growth	-3.423*	-2.129	-1.429
	(1.912)	(5.193)	(1.575)
Constant	-0.256	-3.261***	-0.541***
	(0.262)	(0.405)	(0.199)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4171	3015	3917
Number of countries	141	115	142
Adjusted R^2	0.414	0.417	0.201

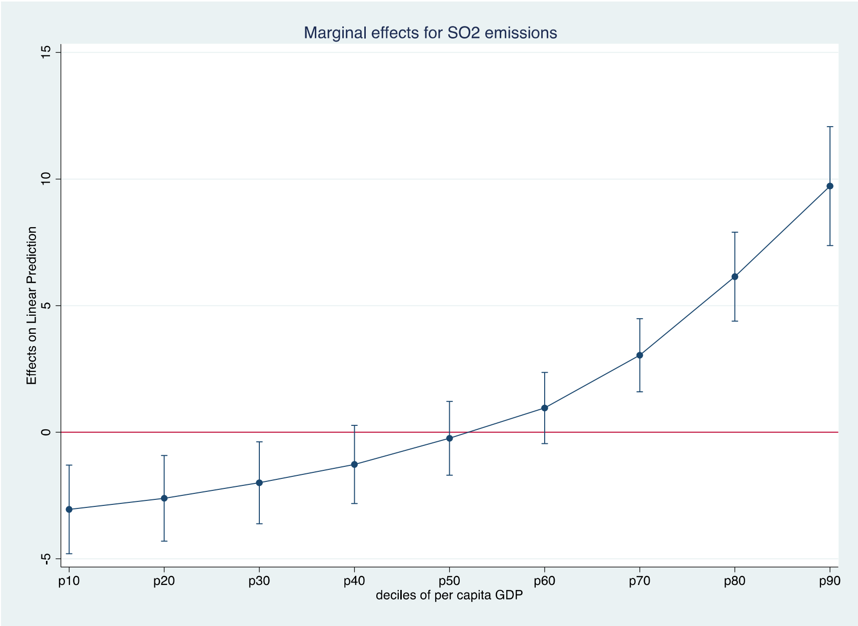
Notes: This table presents the results of a panel fixed effect estimator based on Equation 1. All regressions include country fixed effects and year-specific dummies. The time span is 1960 to 2013 for CO_2, 1960 to 2005 for SO_2, and 1970 to 2012 for N_2O. GDP per capita is divided by 10000 to enhance coefficient readability; Ineq is measured by the net Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2 – Marginal effect on CO_2 emissions of an increase in inequality by deciles of the GDP per capita distribution, based on the estimates in Table 4



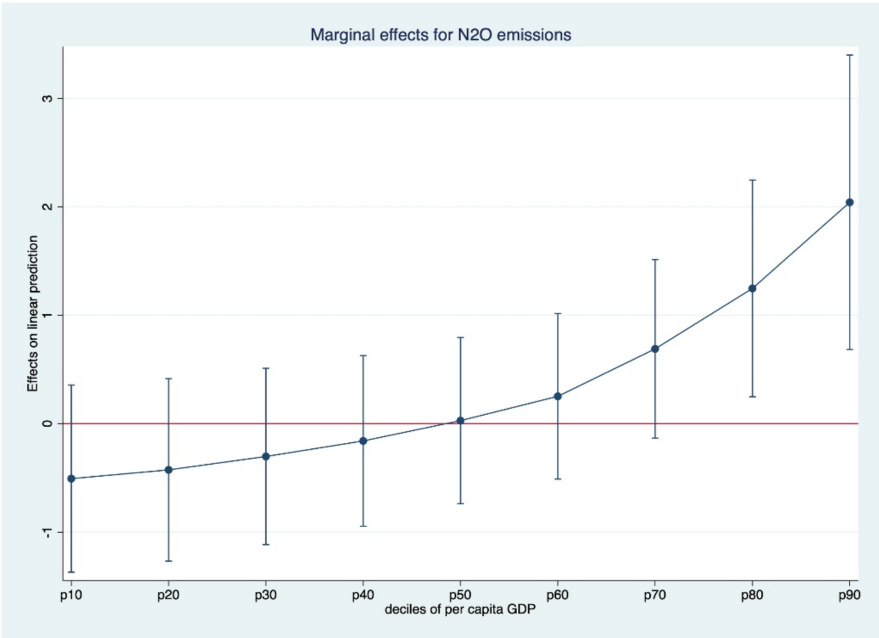
Notes: The x axis represents percentiles of the cross-country distribution of GDP per capita; the y axis reports the marginal effect of inequality for each corresponding level of GDP per capita (derived from Table 4); the vertical bars are the confidence interval of the marginal effect of inequality in correspondence to each income decile.

Figure 3 – Marginal effect on SO_2 emissions of an increase in inequality by deciles of the GDP per capita distribution, based on the estimates in Table 4



Notes: The x axis represents percentiles of the cross-country distribution of GDP per capita; the y axis reports the marginal effect of inequality for each corresponding level of GDP per capita (derived from Table 4); the vertical bars are the confidence interval of the marginal effect of inequality in correspondence to each income decile.

Figure 4 – Marginal effect on N_2O emissions of an increase in inequality by deciles of the GDP per capita distribution, based on the estimates in Table 4



Notes: The x axis represents percentiles of the cross-country distribution of GDP per capita; the y axis reports the marginal effect of inequality for each corresponding level of GDP per capita (derived from Table 4); the vertical bars are the confidence interval of the marginal effect of inequality in correspondence to each income decile.

4.2 Focus on rich countries

The empirical evidence presented in Table 4 corroborates our theoretical prediction that the effect of inequality on emissions depends on the level of income per capita and turns positive and statistically significant only for countries that are sufficiently rich. However, the results are not clear cut for CO_2, and which of the underlying mechanisms prevails, i.e., political economy or aggregation of preferences, remains unclear.

We examine these issues using a subsample of rich countries, which include the OECD founders plus Japan, Finland, Australia and New Zealand, which joined the organization just 12 years after its foundation, and excluding Turkey, which has a level of GDP per capita consistently below the 9th decile.[20] The focus on rich and democratic countries is justified by three facts. First, our theoretical framework and the results of the previous section show that the positive effect of reducing inequality on emissions emerges for rich countries only. Second, in rich countries, we are able to observe environmental policies over a long time span; thus, we can test whether reducing inequality has a positive effect on the political support for these policies. Third, political institutions are stable and similar in OECD countries, thereby reducing possible confounding factors to facilitate a correct interpretation of our results.[21] Recall that for this extension, we use a modified version of Equation 1, which does not include the interaction between *GDP per capita* and *Ineq*. Conceptually, as this group of countries is homogenous in terms of income levels and institutions, there is no reason to let the effect of *Ineq* vary with income.

The estimated coefficients are reported in Table 5, as usual for the three different pollutants. For brevity, we focus our comments on the inequality coefficient.[22] As predicted by our conceptual framework, reduced inequality is always associated with a reduction in GHG emissions when we restrict the sample to rich countries only. Importantly, we also observe a substantial increase in the precision (and the statistical significance) of the estimated coefficient of inequality for CO_2 emissions, which are those with the largest effect on global warming. This result explains why rich countries with low levels of inequality are those more willing to take the lead in climate change negotiations (e.g., Denmark) or enact ambitious carbon taxation (e.g., Sweden).

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[20] The full list of country includes Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Great Britain, United States, Japan, Australia, Finland, and New Zealand.

[21] We also focus on a balanced panel of countries rather than on countries at the 9th and the 10th deciles of the GDP per capita distribution in order to avoid compositional change related to the entry and exit of countries in the top deciles.

[22] Regarding the other coefficients, those associated with the polynomial in GDP per capita are comparable with the ones in Table 3 for CO_2 and N_2O, while they are never statistically significant for sulfur dioxide. Once again, population growth has no significant effect on emissions.

Table 5 – Inequality-augmented EKC models for the restricted sample of OECD founders' countries

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Per capita GDP	1.164***	0.827	0.448**
	(0.210)	(1.099)	(0.165)
Per capita GDP (squared)	-0.212***	-0.275	-0.110**
	(0.051)	(0.283)	(0.0416)
Per capita GDP (cube)	0.012***	0.019	0.007**
	(0.003)	(0.022)	(0.002)
Ineq	2.034**	6.044***	0.880*
	(0.858)	(1.482)	(0.476)
Population growth	-5.189	-7.151	-4.145
	(4.877)	(13.04)	(3.640)
Constant	0.327	-4.849***	-0.488**
	(0.380)	(0.860)	(0.223)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	898	751	817
Number of countries	21	21	21
Adjusted R^2	0.456	0.693	0.710

Notes: This table presents the results of a panel fixed effect estimator. All regressions include country fixed effects and year-specific dummies. The time span is 1960 to 2014 for CO_2, 1960 to 2005 for SO_2, and 1970 to 2012 for N_2O. Per capita GDP is divided by 10000 to enhance coefficient readability. Inequality is measured with the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To quantify the effect of *Ineq* in the subsample of OECD countries, we observe that on average, inequality increased from a value of 0.273 in 1985, when it was at its lowest level, to a value of 0.308 in 2014. However, it remained much lower in the Scandinavian countries (namely, Finland, Denmark, Sweden, and Norway), where the Gini coefficient was 0.201 in 1985 and 0.250 in 2014, than in other OECD founders. Our alternative scenario for quantification computes the average level of emission in OECD founder countries if they had experienced the average variation in the Gini coefficient experienced by Scandinavian countries over the period 1960 up to the year of the last available observation for each pollutant, that is, $\hat{\beta}_{ineq_{oecd}} \times \overline{\Delta ineq}_{scandinavia}$.[23]

The result of this simple exercise shows that if the OECD founder countries had experienced the same variation in inequality over the analysed period as the Scandinavian group,[24] their CO_2 emissions and N_2O emissions would have been 4% and 2% lower, respectively. Similarly, if in the 20 years between 1985 and 2005 the growth in inequality in the OECD founder countries had been comparable to the growth in the Scandinavian area, their SO_2 emissions would have been 9% lower.

To summarize, when we focus on rich countries only, a rise in inequality is associated with an increase in emissions for all pollutants, including CO_2 (and not only SO_2 and N_2O, as in the case of

[23] With $\hat{\beta}_{ineq_{oecd}}$ we refer to the coefficient of inequality obtained in the restricted sample of OECD founders' countries (Table 5), which is equal to 1.939 for Log CO_2, 6.044 for Log SO_2 and 0.822 for Log N_2O.

[24] The yearly variation in the Gini coefficient is different across the pollutant samples and depends on the different time spans. We recall that CO_2 is available for 1960–2013 (53 years), SO_2 for 1960–2005 (45 years) and N_2O for 1970–2012 (42 years).

the full sample). This supports our claim that the effect of inequality on emissions operates via the *political economy channel*. The next section further scrutinizes this claim.

4.3 Focus on environmental policies

The results obtained thus far support the claim that at least in rich countries, the political economy argument prevails over the aggregation argument. Thus, a decrease in inequality, by increasing the income of the median voter, fosters demand for environmental policies. To further investigate this claim, we conduct an additional empirical exercise on the sample of OECD founder countries where we regress seven indices of environmental policies (data available from 1990 onwards) on the usual covariates used in the previous estimates and summarized in Equation 6:

$$Log(EnvPolicy_{it}) = \beta_1 GDPpc_{it} + \beta_2 (GDPpc_{it})^2 + \beta_3 (GDPpc_{it})^3 + \beta_4 Ineq_{it} + \beta_5 \Delta Pop_{it} + \beta_6 \overline{e}_i + \mu_t + \varepsilon_{it}, \qquad (6)$$

where the dependent variable is one of the policy indices developed by the OECD: environmental policy stringency (EPS), market EPS, nonmarket EPS, environmental standards, environmental taxes, environmental tax revenue and tradable permits (see Botta and Kozluk, 2014). *GDPpc*, *Ineq* and *Pop* are—as before—GDP per capita, the Gini index of inequality and population growth. Unlike in the previous estimates, here we employ an OLS regression including among the covariates the presample mean of the emissions indicators, built as the average emissions level from 1975 to 1980 ($\overline{e}_i$). This strategy is employed because the indices of environmental policies are very persistent over time and, in cases such as this, a fixed effect estimator is typically inconsistent (Blundell et al. 2002). Using the presample mean of the dependent variable allows us to account for unobserved country heterogeneity in a more satisfactory way.

The results are shown in Table 6. In all estimates, the negative and statistically significant sign of the Gini coefficient supports the median voter theorem: an increase in inequality, by widening the distance between the median voter's income and the average income, decreases demand for environmental policies. To quantify this effect, we calculate that an increase of one standard deviation in inequality decreases total EPS by 0.380 standard deviations. This is equal to the difference in policy stringency between Japan and Korea in 2014. Comparing market versus nonmarket instruments (the second and third columns), we note that the aggregate figure hides a certain degree of heterogeneity, as the effect of increasing *Ineq* by one standard deviation decreases the stringency of the two indicators by 0.214 and 0.4 standard deviations, respectively. Finally, the fourth to the seventh columns disaggregate the results across the four main policy instruments. When computing the standardized effect, we found that the size of the coefficient of *Ineq* is aligned with the average value for the first three indicators (0.380 std. dev.), while in the case of tradable permits, the standardized effect has a smaller size (-0.194 std. dev.). This empirical test reinforces the idea that the main results of Table 4 are driven by the joint effect that the level and the distribution of income exert through the political economy channel.

Table 6 –Inequality and environmental policies, OECD policy indicators

	(1) EPS	(2) Market EPS	(3) Nonmarket EPS	(4) Standards (stringency)	(5) Taxes (stringency)	(6) Tax revenues (% of GDP)	(7) Tradable permits (stringency)
Per capita GDP	-0.259*	0.335*	-0.863***	-0.964***	0.424**	0.644***	-1.386***
	(0.140)	(0.179)	(0.169)	(0.224)	(0.178)	(0.157)	(0.248)
Per capita GDP (squared)	0.216***	0.007	0.438***	0.488***	-0.143**	-0.151***	0.516***
	(0.051)	(0.065)	(0.063)	(0.076)	(0.066)	(0.041)	(0.105)
Per capita GDP (cube)	-0.024***	-0.005	-0.044***	-0.051***	0.016**	0.011***	-0.051***
	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.003)	(0.012)
Ineq	-3.748***	-1.855***	-5.158***	-5.838***	-2.507***	-4.684***	-2.067***
	(0.393)	(0.454)	(0.500)	(0.686)	(0.480)	(0.532)	(0.579)
Population growth	-1.867	-8.034	1.490	0.174	-6.274	-24.45***	-13.98**
	(4.995)	(6.206)	(5.737)	(8.120)	(5.468)	(5.449)	(6.838)
N_2O (presample mean)	-0.302***	-0.272***	-0.297***	-0.390***	-0.434***	0.008	0.066
	(0.039)	(0.049)	(0.047)	(0.061)	(0.047)	(0.036)	(0.051)
SO_2 (presample mean)	0.246***	0.336***	0.166***	0.442***	0.148***	0.171***	0.224***
	(0.033)	(0.041)	(0.045)	(0.056)	(0.043)	(0.029)	(0.048)
CO_2 (presample mean)	-0.125**	-0.319***	0.015	-0.191**	0.228***	-0.262***	-0.074
	(0.059)	(0.069)	(0.072)	(0.096)	(0.072)	(0.078)	(0.083)
Constant	2.700***	2.007***	3.422***	4.454***	1.372***	4.308***	2.575***
	(0.249)	(0.308)	(0.346)	(0.421)	(0.363)	(0.337)	(0.351)
Country FE	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	676	676	683	683	676	875	683
Adjusted R^2	0.778	0.569	0.755	0.787	0.426	0.441	0.521

Notes: This table presents the results of an OLS regression. All regressions include country fixed effects and the presample mean of the dependent variable computed as the average emissions level from 1975 to 1980. The time span is from 1990 onwards because of the availability of EPS data. Year fixed effects are included. Per capita GDP is divided by 10000 to enhance coefficient readability. Inequality is measured with the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Robustness

This last section presents a series of robustness exercises that address the potential limitations of our empirical setting.

The work by Grunewald et al. (2017), which exploits an empirical framework similar to ours, claims that for the study of the inequality–environment nexus, a group fixed effects (GFE) estimator[25] has to be preferred with respect to individual fixed effects because, in this context, the main sources of unobserved heterogeneity—which are, according to the authors, the rate of adoption of clean

[25] The group fixed effect estimator allows us to control, in linear panel data models, for time-varying and group-specific patterns of unobserved heterogeneity. Group membership and time patterns are not arbitrarily chosen by the analyst but estimated alongside the other parameters of the model. For more details, see Bonhomme and Manresa (2015).

technologies and the structural challenges faced by societies—vary through time and across different regions of the world. To account for this concern, we run an additional set of estimates that include, in addition to the individual fixed effects, a full set of interactions between a time trend and income dummies (one for each decile of the per capita GDP distribution). The results, reported in Table 7, remain qualitatively unchanged with respect to those of our preferred specification in Table 4: inequality exerts the expected effect on emissions per capita and is statistically significant only in the case of SO_2 and N_2O emissions.

Furthermore, we take stock of the previous literature by adding several possible confounding factors. First, in line with the work by Hubler (2017), we control for the impact of FDI-induced capital accumulation and international technological spillovers (proxied here by FDI and trade openness), which are two of the main factors behind the transition from an agriculture-based society towards an industry-based society, that is, the inflection point of the EKC. Second, we control for the type of political regime, considered since the work by Magnani (2000) and Boyce (1994) as one of the main mediating factors behind the inequality–environment nexus. In majoritarian democracies, in fact, the growing demand for environmental protection stemming from a reduction in inequality and/or an increase in per capita income is more likely to translate into strict environmental policies through the legislative process than in autocratic regimes, where policy formation may be in the hands of small oligarchies that benefit from polluting activities (Boyce, 1994). To do so, we include in the analysis an ordinal variable that ranges from 1 (most autocratic) to 8 (most democratic).

Due to limited data availability, including these regressors implies losing many observations. Specifically, *Trade Openness* registers the most missing values for years before the 1990s for African countries, East European countries and Russia and Taiwan. Many countries are completely removed from the analysis because of a lack of observations for both *FDI* and *Trade Openness* (e.g., Guinea, Haiti, and Lesotho), while for Luxembourg, *FDI* data are available only for years from 2002.

The regression results for these additional estimates are presented in the first three columns of Table 8. Overall, the results show that the inclusion of additional covariates does not alter our main evidence: the effects of *Ineq*, *GDP per capita* and their interaction are qualitatively unchanged, and their significance level is very similar to that in Table 4. FDI investment and trade openness are never statistically significant, a result in line with the finding of Hubler (2017). Similarly, the democracy dummies are never statistically significant. For comparison, the last three columns of Table 8 replicate the results of Table 4 in the smaller sample used for this robustness exercise. Compared to the results in Table 4, those in Table 8 show no significant differences.

A final series of robustness checks are presented in Appendix C.

First, we address the potential issue of integrated time series within the panel. As mentioned in Section 3.3, the EKC literature suggests either running panel unit root tests (as in Moon and Perron, 2004, or Bai and Ng, 2004) to assess whether CO_2, SO_2 or GDP per capita are integrated variables (for more details on this topic, see Wagner 2008) or, alternatively, using models that account for the presence of integrated time series by first taking the average of original data over time or by using a between estimator (Stern, 2010). Following this last approach, in Table C.1, we present a robustness exercise obtained by computing the 5-year average of both the dependent and independent variables and replicate the analysis from Table 4, our benchmark estimates. The regression results show that the potential presence of integrated time series does not alter the main evidence found in Section 4.1. The only relevant difference is the coefficient for population growth, which here exhibits a negative and statistically significant effect in the case of CO_2 emissions. Similar results, available upon request, are obtained when we first-difference the data.

In Table C.2, we run the model of Equation 1 using the "All the Ginis" (Milanovic, 2013) indicator of inequality instead of the SWIID index to test the sensitivity of our results to the use of a different proxy of inequality. Unlike the SWIID, this dataset draws information on nine different sources of Gini coefficients to offer a unique measure of inequality. To do so, the authors follow an approach called the rule of precedence, which establishes a hierarchy among the nine data sources according to the principle that individual long-term country studies based on household survey microdata are preferred over wider datasets (i.e., those including more than one country) based on microdata or grouped data. As a result, the least preferred sources are used to compile the "All the Ginis" index only when data from better sources are not available. When we employ this indicator instead of the preferred SWIID index (see Table C.2), the results of our baseline specification are mostly confirmed, with the only difference being for N_2O, for which the coefficient of Gini is statically significant and has the expected negative sign.

Table C.3 addresses the potential impact on the estimation results of the process of interpolation adopted to impute the missing values on both the dependent and independent variables (see Section 3.1 and Appendix A). To do so, we run the main estimates of Table 4 and introduce, among the regressors, a set of dummies—one for each variable included in Equation 1—which assumes a value equal to 1 in correspondence to each imputed missing value in the original dataset. These dummy variables control for the potential measurement error introduced by the interpolation procedure in the regression framework. This empirical test confirms the main evidence of Table 4, supporting the strategy that we adopted to deal with missing data.

Table 7 – Baseline specification with a time trend

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Per capita GDP	1.058***	0.285	0.243
	(0.206)	(0.374)	(0.174)
Per capita GDP (squared)	-0.278***	-0.492***	-0.126***
	(0.049)	(0.126)	(0.029)
Per capita GDP (cube)	0.018***	0.037***	0.008***
	(0.003)	(0.011)	(0.001)
Ineq	0.145	-3.305***	-0.593
	(0.505)	(0.836)	(0.389)
Ineq x Per capita GDP	0.383	4.160***	0.820***
	(0.341)	(0.533)	(0.258)
Population growth	-3.526*	-2.502	-2.026
	(1.881)	(4.004)	(1.539)
Constant	-6.835	31.11***	23.23***
	(5.579)	(9.611)	(5.863)
Year*decile of GDP per capita	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	No	No	No
Observations	4171	3015	3917
Number of countries	141	115	142
Adjusted R^2	0.432	0.460	0.197

Note: This table presents the results of a panel fixed effect estimator. All regressions include country fixed effects and a time trend by deciles of per capita income, computed based on the mean per capita income by country over the period. Per capita GDP is divided by 10000 to enhance coefficient readability. Inequality is measured with the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 –Baseline specification including trade openness, incoming FDI and Polity2 levels as control variables

				Baseline specification (Eq. 1)		
	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O	(7) Log of CO_2	(8) Log of SO_2	(9) Log of N_2O
Per capita GDP	0.896***	-0.0430	0.144	0.925***	-0.051	0.163
	(0.208)	(0.471)	(0.183)	(0.209)	(0.486)	(0.187)
Per capita GDP (squared)	-0.252***	-0.613***	-0.099***	-0.256***	-0.621***	-0.105***
	(0.045)	(0.160)	(0.030)	(0.047)	(0.162)	(0.031)
Per capita GDP (cube)	0.018***	0.064***	0.006***	0.018***	0.066***	0.00751***
	(0.004)	(0.019)	(0.002)	(0.004)	(0.021)	(0.002)
Ineq	0.123	-2.997***	-0.404	0.203	-3.022***	-0.372
	(0.494)	(0.874)	(0.437)	(0.519)	(0.907)	(0.446)
Ineq x Per capita GDP	0.0368	3.992***	0.669	0.014	3.995***	0.654
	(0.396)	(0.698)	(0.411)	(0.375)	(0.744)	(0.430)
Population growth	-4.337**	-3.389	-1.076	-3.846**	-3.812	-0.915
	(1.910)	(4.928)	(1.500)	(1.725)	(4.738)	(1.482)
Trade Openness	0.001	0.0015	0.001	-	-	-
	(0.001)	(0.001)	(0.001)			
FDI (incoming)	0.0127*	-0.016	0.004	-	-	-
	(0.007)	(0.014)	(0.006)			
Polity lev. 1	0.105	-0.008	-0.010	-	-	-
	(0.118)	(0.154)	(0.063)			
Polity lev. 2	0.015	-0.078	-0.064	-	-	-
	(0.077)	(0.158)	(0.051)			
Polity lev. 3	0.022	0.138	-0.043	-	-	-
	(0.065)	(0.125)	(0.049)			
Polity lev. 4	-0.068	0.0536	-0.028	-	-	-
	(0.068)	(0.114)	(0.058)			
Polity lev. 5	0.003	0.0131	0.016	-	-	-
	(0.066)	(0.101)	(0.054)			
Polity lev. 6	0.0915	0.138	0.009	-	-	-
	(0.056)	(0.092)	(0.050)			
Polity lev. 7	0.020	0.008	-0.013	-	-	-
	(0.054)	(0.084)	(0.052)			
Constant	-0.238	-3.211***	-0.649***	0.018	-3.344***	-0.551***
	(0.274)	(0.526)	(0.206)	(0.245)	(0.440)	(0.169)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3321	2306	3293	3321	2306	3293
Number of countries	132	111	134	132	111	134
Adjusted R^2	0.401	0.489	0.188	0.381	0.476	0.183

Notes: This table presents the results of a panel fixed effect estimator. All regressions include country fixed effects and year-specific dummies. The time span is 1960 to 2013 for CO_2, 1960 to 2005 for SO_2, and 1970 to 2012 for N_2O. Polity level 1 includes Polity indicators from -10 to -8; Polity level 2 includes the Polity indicator with a value of -7; Polity level 3 includes Polity indicators from -6 to -5; Polity level 4 includes Polity indicators from -4 to 0; Polity level 5 includes Polity indicators from 1 to 5; Polity level 6 includes Polity indicators from 6 to 7; Polity level 7 includes the Polity indicator with a value of 8; Polity level 8 includes Polity indicators from 9 to 10. Per capita GDP is divided by 10000 to enhance coefficient readability. Inequality is measured with the Gini coefficient. Columns 7 to 9 of the table show the regression results using the baseline specification of Equation 1 and the restricted sample. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Concluding remarks

The aim of this paper is to offer a novel and more comprehensive perspective on the relation between environmental quality, inequality and economic growth. To do so, we augment a standard EKC model with an inequality term and its interaction with per capita income. Our preliminary results present new evidence on the inequality–environment nexus. First, we show that this relationship depends on the level of income. For countries below the 6^{th} decile of income distribution, a decrease in inequality is on average associated with higher SO_2 and N_2O emissions. After this threshold, a reduction in inequality is good for the environment. For CO_2, the effect of a reduction in inequality on emissions emerges only in rich countries. Second, our analysis supports the hypothesis that the *political economy argument* prevails over the *aggregation argument*. In other words, inequality—by increasing the wealth of the median voter—influences emissions by supporting demand for stringent environmental policies.

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Appendix A: Data

Dealing with different pollutants' sample sizes as well as with missing values, has been two majors challenges for our analysis. As presented in Table 2, the length of the data set varies across pollutants: 1960-2014 for CO_2; 1960-2005 for SO_2 and 1970-2012 for N_2O. Also, country coverage depends on the pollutant considered, ranging from 115 countries for SO_2 to 141 and 142 for CO_2 and N_2O respectively. Despite the differences in terms of years and countries coverage, which depend on data availability, we have chosen to keep all the available series to maximize the number of observations for each emission.

We detected a large share of missing values, precisely 34% for CO_2, 60% for SO_2 and 29% for N_2O. Missing observations for the Gini coefficient and GDP were 67% and 34%, respectively, while population is missing for 35% of the observations. We notice that OECD countries did show a significantly lower percentage of missing values compared to non-OECD ones; for example, for CO_2, the share of missing values was barely 7% for OECD countries and 39% for non-OECD ones and GDP values were missing for 5% of the former group and 50% of the latter. Population did show similar shares while N_2O was missing for the 37% of OECD countries and 51% of non-OECD; finally, SO_2 did present the highest shares: 56% for OECD and 88% for non-OECD.

If either the Gini or the GDP or the population was completely missing for a country, we dropped that country from the estimation sample. We try to impute some missing observation only when they were internal values in a time series by imputing the moving average of the two adjacent years, and never filled missing observation at the beginning or at the end of a time series. With our simple imputation method, we could recover 18% of the observations for CO_2 and SO_2 and 20% of N_2O ones. Moreover, we recovered the 22% of observations for our key explanatory variable, the SWIID Gini index, as well as the 20% of GDP and population data. To provide further robustness to our results, we also run the main regression model for each pollutant including a dummy variable which takes value 1 if the observation is imputed and 0 otherwise. Those results are available in Table C3.

Appendix B – Specification tests

We use the following standard goodness of fit measures to compare the five different model specifications presented in Table 2:

- the Adjusted R-squared, is a modified version of the standard R-squared that accounts for the number of predictors in the model,[26] and represents the proportion of variance of the dependent variable which can be predicted by the regressors (i.e., the higher is the Adjusted R-squared value, the higher is the expected predictive power of the independent variables).
- The Akaike information criteria (AIC) and the Bayes information criteria (BIC), which estimate how distant the likelihood function of the fitted model is from the real likelihood function of the data. When comparing two models using the same set of data, AIC and BIC can be used for model selection, and the model with the lower values of these criteria is the preferred one.[27] Note that, as for the adjusted R-squared, the AIC and BIC information criteria adds a penalty for the number of predictors.

  For the sake of completeness, the Tables B.1 to B.4 report the estimated results of equations 2 to 5.

Table B.1 – Log-lin cubic EKC (equation 2 of table 2)

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Per capita GDP	1.090***	1.602***	0.516***
	(6.411)	(0.418)	(3.611)
Per capita GDP (squared)	-0.290***	-0.625***	-0.126***
	(-6.203)	(0.125)	(-4.262)
Per capita GDP (cube)	0.021***	0.053***	0.009***
	(5.262)	(0.013)	(4.161)
Population growth	-3.850*	-4.417	-2.242
	(-1.95)	(7.671)	(-1.24)
Constant	-0.297*	-4.831***	-0.806***
	(-1.87)	(0.272)	(-8.81)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4171	3015	3917
Number of countries	141	115	142
Adjusted R^2	10.38	0.282	9.583

Note: This table presents the results of a panel fixed effect estimator based on Eq. 2 of table 2. All regressions include country fixed effects and year-specific dummies. The time span is: 1960 to 2013 for CO2; 1960 to 2005 for SO2; 1970 – 2012 for N2O. Per capita GDP has been divided by 10000 to enhance coefficients readability. Inequality is measured using the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[26] The main drawback of the R squared is that it never decreases when a new independent variable is added to a regression equation. In contrast, when adding a new regressor, the adjusted R-squared – being adjusted for the degrees of freedom – can go up or down, and it increases only if the *t* statistic on the new variable is greater than one in absolute value (Woolridge 2015, p. 202).

[27] See Akaike (1974); Raftery (1995) and Schwarz (1978).

Table B.2 - Log-lin cubic inequality augmented EKC (equation 3 of table 2)

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Per capita GDP	1.089***	1.602***	0.516***
	(6.392)	(0.418)	(3.601)
Per capita GDP (squared)	-0.291***	-0.625***	-0.126***
	(-6.141)	(0.125)	(-4.201)
Per capita GDP (cube)	0.021***	0.0533***	0.009***
	(5.213)	(0.0131)	(4.101)
Ineq.	0.226	-0.0227	-0.023
	(0.481)	(0.810)	(-0.061)
Population growth	-3.833*	-4.422	-2.246
	(-1.981)	(7.620)	(-1.241)
Constant	-0.478*	-4.822***	-0.762***
	(0.239)	(0.371)	(0.174)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4171	3015	3917
Number of countries	141	115	142
Adjusted R^2	10.43	0.281	9.380

Note: This table presents the results of a panel fixed effect estimator based on Eq. 3 of table 2. All regressions include country fixed effects and year-specific dummies. The time span is: 1960 to 2013 for CO2; 1960 to 2005 for SO2; 1970 – 2012 for N2O. Per capita GDP has been divided by 10000 to enhance coefficients readability. Inequality is measured using the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3 - Log-log squared EKC (equation 4 of table 2)

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Log of Per capita GDP	0.392***	-0.0697	0.206**
	(5.160)	(0.266)	(2.131)
Log of Per capita GDP (squared)	-0.113***	-0.300**	-0.0194
	(-4.101)	(0.0932)	(-0.690)
Population growth	-4.223**	-11.07	-2.631
	(-2.190)	(7.422)	(-1.401)
Constant	0.900***	-3.499***	-0.334***
	(5.981)	(0.338)	(-4.420)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4171	3015	3917
Number of countries	141	115	142
Adjusted R^2	12.11	0.245	9.025

Note: This table presents the results of a panel fixed effect estimator based on Eq. 4 of table 2. All regressions include country fixed effects and year-specific dummies. The time span is: 1960 to 2013 for CO2; 1960 to 2005 for SO2; 1970 – 2012 for N2O. Per capita GDP has been divided by 10000 to enhance coefficients readability. Inequality is measured using the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4 - Log-log squared EKC (equation 5 of table 2)

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Log of Per capita GDP	0.522***	0.323	0.249**
	(5.962)	(0.261)	(2.590)
Log of Per capita GDP (squared)	-0.172***	-0.550***	-0.039
	(-6.341)	(0.106)	(-1.130)
Log of Per capita GDP (cube)	-0.046**	-0.165***	-0.015
	(-3.420)	(0.031)	(-1.521)
Population growth	-2.728*	-5.079	-2.135
	(-1.680)	(7.751)	(-1.201)
Constant	0.915***	-3.441***	-0.318***
	(6.430)	(0.334)	(-4.291)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4171	3015	3917
Number of countries	141	115	142
Adjusted R^2	12.06	0.322	9.045

Note: This table presents the results of a panel fixed effect estimator based on Eq. 5 of table 2. All regressions include country fixed effects and year-specific dummies. The time span is: 1960 to 2013 for CO2; 1960 to 2005 for SO2; 1970 – 2012 for N2O. Per capita GDP has been divided by 10000 to enhance coefficients readability. Inequality is measured using the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C – Robustness

Table C.1 - Baseline model with dependent and independent variables collapsed in 5 years averages.

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Per capita GDP	0.980***	-0.820**	0.153
	(0.217)	(0.354)	(0.173)
Per capita GDP (squared)	-0.297***	-0.371***	-0.116***
	(0.047)	(0.092)	(0.029)
Per capita GDP (cube)	0.021***	0.031***	0.008***
	(0.003)	(0.008)	(0.002)
Ineq	0.196	-2.978***	-0.482
	(0.561)	(1.042)	(0.470)
Ineq x Per capita GDP	0.396	4.883***	0.871***
	(0.340)	(0.660)	(0.278)
Population growth	-1.398**	-0.537	-0.127
	(0.562)	(1.522)	(0.555)
Constant	-0.338	-3.525***	-0.664***
	(0.254)	(0.413)	(0.199)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	924	717	894
Number of countries	141	115	142
Adjusted R^2	0.467	0.409	0.232

Notes: This table presents the results of a panel fixed effect estimator based on Eq. 1, where we collapsed both dependent and independent variables in 5-year averages to exclude stationarity issues. All regressions include country fixed effects and year-specific dummies. The time span is: 1960 to 2013 for CO_2; 1960 to 2005 for SO_2; 1970 to 2012 for N_2O. Per capita GDP has been divided by 10000 to enhance coefficients readability. Inequality is measured using the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2 - Regression results of Table 4 with "All the Ginis" Gini coefficient

				Baseline specification (eq.1)		
	(1)	(2)	(3)	(7)	(8)	(9)
	Log of CO_2	Log of SO_2	Log of N_2O	Log of CO_2	Log of SO_2	Log of N_2O
Per capita GDP	1.156***	-0.013	0.333**	0.983***	-0.552	0.215
	(0.198)	(0.302)	(0.142)	(-0.219)	(-0.354)	(-0.161)
Per capita GDP (squared)	-0.335***	-0.469***	-0.126***	-0.301***	-0.444***	-0.122***
	(0.054)	(0.096)	(0.029)	(-0.053)	(-0.099)	(-0.030)
Per capita GDP (cube)	0.024***	0.039***	0.009***	0.022***	0.040***	0.009***
	(0.004)	(0.009)	(0.002)	(-0.004)	(-0.010)	(-0.002)
Gini (All)	0.003	-2.795***	-0.671**	-	-	-
	(0.409)	(0.737)	(0.329)			
Gini (All) x Per capita GDP	0.134	2.986***	0.517**	-	-	-
	(0.251)	(0.611)	(0.225)			
Gini (Swiid)	-	-	-	0.173	-3.500***	-0.783
				(-0.528)	(-0.908)	(-0.51)
Gini (Swiid) x Per capita GDP	-	-	-	0.235	4.364***	0.785***
				(-0.371)	(-0.587)	(-0.29)
Population growth	-1.806	-6.065	-2.993	-3.099	-4.683	-1.891
	(2.221)	(6.401)	(1.983)	-1.9	-6.302	-1.735
Constant	-0.598**	-3.506***	-0.483***	-0.502*	-3.331***	-0.457**
	(0.256)	(0.446)	(0.171)	(-0.27)	(-0.433)	(-0.226)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4110	2814	3897	3643	2814	3507
Number of countries	137	112	138	137	112	138
Adjusted R^2	0.416	0.398	0.198	0.41	0.421	0.193

Notes: This table presents the results of a panel fixed effect estimator based on Eq. 1, where we use the Gini coefficient variable from "All the Ginis" (World Bank). All regressions include country fixed effects and year-specific dummies. The time span is: 1960 to 2013 for CO2; 1960 to 2005 for SO2; 1970 – 2012 for N2O. Per capita GDP has been divided by 10000 to enhance coefficients readability. Inequality is measured using the Gini coefficient. The last three column of the table show the regression results using the baseline specification of eq. 1 on the restricted sample. Standard errors clustered by country in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table C.3 – Specification augmented with a set of missing-observations dummy variables

	(1) Log of CO_2	(2) Log of SO_2	(3) Log of N_2O
Per capita GDP	0.897^{***}	-0.417	0.170
	(0.214)	(0.352)	(0.163)
Per capita GDP (squared)	-0.282^{***}	-0.509^{***}	-0.113^{***}
	(0.047)	(0.100)	(0.029)
Per capita GDP (cube)	0.021^{***}	0.044^{***}	0.008^{***}
	(0.003)	(0.009)	(0.002)
Ineq	-0.085	-3.812^{***}	-0.619
	(0.530)	(0.944)	(0.458)
Ineq x Per capita GDP	0.465	4.796^{***}	0.849^{***}
	(0.345)	(0.560)	(0.260)
Population growth	-3.441^{*}	-2.047	-1.442
	(1.915)	(5.156)	(1.578)
Constant	-0.254	-3.268^{***}	-0.539^{***}
	(0.263)	(0.402)	(0.199)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Dummy missing values	Yes	Yes	Yes
Observations	4171	3015	3917
Number of countries	141	115	142
Adjusted R^2	0.414	0.419	0.201

Note: This table presents the results of a panel fixed effect estimator based on equation 1. All regressions include country fixed effects and year-specific dummies. The time span is: 1960 to 2013 for CO_2; 1960 to 2005 for SO_2; 1970 – 2012 for N_2O. Dummy variables assumes value 0 if the observation is not missing and 1 if the observation is missing. Per capita GDP has been divided by 10000 to enhance coefficients readability. Inequality is measured using the Gini coefficient. Standard errors clustered by country in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Corso Magenta 63, Milano – Italia

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