Fondazione Eni Enrico Mattei

Income Inequality and the Environmental Kuznets Curve

Simone Borghesi

NOTA DI LAVORO 83.2000

Corso Magenta, 63, 20123 Milano, tel. +39/02/52036934 – fax +39/02/52036946
E-mail: letter@feem.it
C.F. 97080600154

1. Introduction

The relationship between environmental degradation and per capita income has attracted much attention in the literature during the last decade. In the early 1990s, some contemporaneous studies found that several indices of air and water pollution first increase and then decrease as per capita income grows (Panayotou 1993, Shafik 1994, Selden and Song 1994, Grossman and Krueger 1994). This "bell-shaped" relationship was called environmental Kuznets curve after Simon Kuznets (Kuznets, 1955) who was the first to observe a similar relationship between inequality and per capita income (the so-called Kuznets curve). The literature on the environmental Kuznets curve (henceforth EKC) has grown exponentially in the last three years.[1] Recent studies have tried to overcome the limitations of early contributions by using new data sets, new functional forms and more refined econometric techniques. Moreover, some authors (e.g. Unruh and Moomaw, 1998, Kaufman et al., 1998, Suri and Chapman, 1998) have started to question the emphasis on income growth to explain environmental degradation and argued that other explanatory variables should be included in the models. Among these studies, only few works (Torras and Boyce, 1998, Scruggs, 1998, Magnani, 2000, Marsiliani and Renström, 2000, Ravallion et al., 2000) have examined how inequality can affect the environment-income relationship getting mixed or conflicting results. The present paper intends to contribute to this literature bringing new evidence to stimulate discussion on the role of income distribution in the environmental problems. Taking carbon dioxide (CO_2) as indicator of environmental degradation, this work addresses the following question: what is the impact of inequality on CO_2 emissions and on the CO_2-income relationship?

The following section provides an overview of the literature on the environmental impact of inequality. Section 3 describes the data used in the empirical analysis. Section 4 examines the environment-income relationship when inequality is not taken into account. This provides the benchmark for section 5 where the empirical analysis is repeated introducing inequality in the model to answer the question above. Section 6 summarizes the main findings and indicates future lines of research.

[1] See, for instance, Barbier (1997) and Borghesi (1999) for recent surveys of the literature on this topic.

2. The impact of inequality on environmental degradation

2.1. Theoretical arguments

Boyce (1994) was the first author to investigate how inequality affects environmental degradation from the theoretical viewpoint. He set forth the hypothesis that greater inequality may increase environmental degradation in two ways:

1. via impacts on the rate of time preference
2. via the cost-benefit analysis of environmentally degrading activities.

As to the first point, Boyce (1994) argues that a greater inequality increases the rate of environmental time preference (i.e. reduces concern for the future of the earth) for both poor and rich. On the one hand, when inequality increases, the poor tend to overexploit natural capital, since they perceive it as the only resource that they have at disposal and an immediate source of income that can help them secure their day-to-day survival.[2] On the other hand, economic inequality is often associated with political instability and risk of revolts. This leads rich people - who should bear most of the financial costs of protecting the environment - to prefer a policy of exploiting the environment and investing the returns abroad (where political uncertainty is lower) rather than investing in the defense of local natural resources. Thus, according to Boyce an increase in inequality induces both rich and poor to degrade more the environment they live in.

As to the second point, Boyce (1994) states that wealth and power are highly correlated in determining social decisions. In an unequal society, rich people are likely to have large political power and can heavily influence decisions on environmentally damaging projects. Such decisions are based on cost-benefit analysis, more precisely on the competition between those who benefit from the environmentally destructive action ("the winners") and those who bear the costs of it ("the losers"). Boyce (1994) argues that rich people are generally the winners, while poor people tend to be the losers of the investments that have an ecological impact.[3] As a consequence, economic inequality - affecting the distribution of power - may enhance the possibility of environmentally damaging projects and

[2] In our opinion, however, this argument is more appropriate to describe the impact of greater poverty (rather than inequality) on the environment.

[3] In an unequal society rich people can reap most of the benefits of exploiting natural resources (in terms of profits), while poor people often suffer most of the correspondent ecological costs since they rely more heavily on natural resources for their subsistence.

investments since it "reinforces the power of the rich to impose environmental costs on the poor" (Ravallion et al., 2000, p.6). Moreover, Boyce (1994) claims that inequality affects also the monetary valuation of costs and benefits of environmentally damaging projects. Such valuation depends on the willingness to pay of the agents, which in turn depends on their ability to pay and thus on the initial distribution of endowments.

Scruggs (1998) has recently criticized the hypotheses set forth by Boyce. The author claims that there is no necessary causal link between inequality and environmental degradation and that the former may or may not increase the latter. Scruggs states that the second argument proposed by Boyce (i.e. the influence via cost-benefit analysis) is based on two wrong assumptions. First, it assumes that a democratic social choice criterion leads to higher environmental protection than a non-democratic decision process (i.e. a power-weighted social decision rule), while evidence suggests that this is not necessarily true. Second, it seems to imply that rich people prefer more degradation than the poor, whereas "evidence indicates that better off members of society tend to have higher environmental concern than those with lower incomes" (Scruggs, 1998, p.260).[4]

Marsiliani and Renström (2000) have recently examined how inequality affects political decisions on environmental protection. Using an overlapping-generations model, they show that the higher the level of inequality in terms of median-mean distance, the lower the pollution tax set by a majority elected representative. According to the authors, in fact, inequality induces redistribution policies that distort economic decisions and lower production. It follows that the consumption-possibilities frontier moves inward and if the environment is a normal good "this causes any individual to prefer more private consumption in relation to the environment" (Marsiliani and Renström, 2000, p.32).Thus, inequality may be negatively correlated with environmental protection as it leads to less stringent environmental policies.

Ravallion et al. (2000) also look at the effects of income distribution on environmental degradation and claim that the relative impact of rich and poor people on the environment is a priori ambiguous. The authors argue that each individual has an implicit demand function for carbon emissions since the consumption of almost every good implies some emissions either directly (via consumption) or indirectly (via its production). They call marginal propensity to emit (MPE)

[4]In our opinion, it would be more correct to say that better off members of society "can afford" to have higher environmental concern than the poor. Boyce (1994, p.174) makes this point clearly when he distinguishes willingness and ability to pay.

the derivative of this demand function with respect to income. If poor people have a higher MPE than rich ones, a redistribution policy that reduces inequality will increase carbon emissions. Viceversa, if poor people have a lower MPE than better-off classes, reducing inequality will also decrease the emissions level. It is difficult to say a priori which of these two effects can prevail. On the one hand, poor people generally devote their extra income to food and clothing rather than goods with large emission rates, such as motor vehicles, hence their MPE should be lower than that of the rich. On the other hand, they tend to use energy less efficiently than the rich, which entails a higher MPE. The same argument applies to inequality across countries: "reducing inequality between countries might well increase global warming, by redistributing income from countries with a low marginal propensity to emit carbon dioxide to those with a high one" (Ravallion et al., 2000, p.2). In general, therefore, the impact of inequality on emissions is ambiguous and depends on whether the MPE rises or falls as income grows, that is, on the second derivative of the CO_2-income function.

Beyond these theoretical arguments, we can also find some other causal links between inequality and environmental degradation. Much of the theoretical environmental literature has stressed the need of cooperative solutions to environmental problems. In an unequal society this is more difficult to achieve than in an equal society since there are generally more conflicts among the political agents (government, trade unions, lobbies etc...) on many social issues. In this sense, greater inequality can contribute to increase environmental degradation.[5]

The two separate literatures on the Kuznets curve and the EKC provide another possible explanation for the environmental impact of inequality. Barro (1999) has recently showed that a greater inequality can have a differential impact according to the nation's income: it lowers the growth rate in poor countries and increases it in rich ones. At the same time, de Bruyn et al. (1998) have found that income growth is positively related with CO_2 emissions in four OECD countries.[6] These findings jointly suggest that higher inequality may increase CO_2 emissions in rich countries through an increase in their growth rate.

So far we conjectured the possible structural links between inequality and the environment from the theoretical viewpoint. Let us now turn to the empirical

[5] For global pollutants like CO_2 this argument applies better to inequality across countries than within nations since world-wide ecological problems require international cooperation more than national policies.

[6] Note that de Bruyn et al. (1998) differ from the standard EKC literature since they estimate environmental degradation as a function of income growth rather than per capita income.

findings obtained by the current literature on this relationship.

2.2. Empirical findings of the literature

Torras and Boyce (1998) examine a set of water and air pollution variables other than carbon dioxide. Using the Global Environment Monitoring System (GEMS) data originally adopted by Grossman and Krueger (1995), the authors analyze a panel of countries in the period 1977-91.[7] To test the arguments set forth by Boyce (1994) they introduce three explanatory variables that can proxy for power inequality within a country: economic inequality (Gini index), adult literacy rates (LIT) and an aggregate of political rights and civil liberties (RIGHTS). Thus, their econometric model looks as follows:

$$POL_{it} = \alpha + \beta_1 Y_{it} + \beta_2 (Y_{it})^2 + \beta_3 (Y_{it})^3 + \delta_1 GINI_i + \delta_2 LIT_i + \delta_3 RIGHTS_i + \gamma_i Z_i + \varepsilon_{it}$$

where: POL is the pollution variable being tested, Y is per capita income and Z a vector of geographical covariates.[8]

The equation is estimated by ordinary-least squares. As the authors claim, in this case it is not possible to use a fixed effect model since "the power inequality variables have unique values for each country" (Torras and Boyce, 1998, p.151). Comparing estimations with and without the three power inequality variables, the authors find that the statistical significance of income generally falls when power inequality is taken into account. Torras and Boyce obtain mixed results on the environmental impact of income inequality: the Gini coefficient is positive for some environmental indicators and negative for others. Moreover, it is statistically significant in both high- and low-income countries for only one of the seven environmental indicators.

To test the hypothesis that inequality affects the environment, Scruggs (1998) performs two cross-country empirical analyses using pooled models. In the first one the dependent variable is the concentration of four different pollutants (sulfur dioxide, particulate matter, fecal coliform and dissolved oxygen) in a panel of 22 up to 29 countries. The econometric model being tested is:

$$POL_{it} = \alpha + \beta_1 \log Y_{it} + \beta_2 \log(Y_{it})^2 + \delta_1 GINI_{it} + \delta_2 DEMOCRACY_{it} + \varepsilon_{it}$$

[7] The panel is composed of 58 countries for water pollution data and of 19 up to 42 countries for air pollution data.

[8] The vector includes dummies that account for the geographical features of the area where pollution is monitored, indicating whether the monitoring station is located in central cities, coastal zones, industrial and/or residential sites.

where $DEMOCRACY$ is the average of Gastil (1989) freedom ranking in the period 1980-89.[9]

The second investigation examines the impact of several variables on a composite index of environmental quality ($ENVQ$) in a panel of 17 OECD countries. This index is constructed by combining five pollution indicators.[10] In this case Scruggs tests the following model:

$$ENVQ_i = \alpha + \beta_1 \log Y_i + \beta_2 \log(Y_i)^2 + \delta_1 GINI_i + \delta_2 DENSITY_i + \\ + \delta_3 NUCLEAR_i + \varepsilon_i$$

where $DENSITY_i$ is the population density of country i and $NUCLEAR_i$ is the percentage of nuclear power in the nation's energy supply.[11]

In the first analysis, the Gini coefficient turns out to be statistically significant at 10% level for only half of the pollutants being tested and even in these cases, Scruggs gets conflicting results: greater inequality increases environmental degradation for one environmental indicator (dissolved oxygen), whereas the opposite holds for the other indicator (particulates). In the second analysis, either inequality decreases environmental degradation or its impact on the environment is nearly zero. These results seem to confirm the author's viewpoint that inequality is not necessarily related to environmental degradation. The outcome of the second analysis, however, may be affected by the way the composite index of environmental quality is constructed since, as the author also points out, it disregards many pollutants as well as recycling policies and nature's assimilative capacity. In what follows we prefer, therefore, to focus attention on a unique pollutant, carbon dioxide, which contributes to global warming more than any other pollutant.

Magnani (2000) has recently examined the impact of inequality on R&D expenditures for the environment (e) that are taken "as proxy for the intensity of public engagement in environmental problems" (Magnani, 2000, p.438). For this purpose, the author tests the following non-linear model:

$$e_{it} = \alpha + \beta_1 Y_{it} + \beta_2 (Y_{it})^2 + \beta_3 r_{it} + \beta_4 (Y_{it} * r_{it}) + \beta_5 t + \varepsilon_{it}$$

where r_{it} is a measure of income inequality.

[9] When environmental degradation is measured by sulfur dioxide, Scruggs (1998, p.267-'8) includes also a dummy for the period, whereas when is measured by particulate matter he introduces a dummy for the type of monitoring site.

[10] They are: municipal waste, fertilizer use, and emissions of sulfur dioxide (SO_2), nitrous oxide (NO_x) and carbon dioxide (CO_2).

[11] We omit the time subscript t since the data set used for this second analysis is apparently made of 17 observations, that is, one per each country (Scruggs, 1998, p.270, table 2). Note that the $DEMOCRACY$ variable has been ruled out since it has the same value in all the OECD countries being analyzed.

The author presents estimation results obtained by pooled ordinary least squares, random effects and fixed effects models. The latter specification, however, is mainly neglected as the Hausman test does not reject the null hypothesis of no difference between random and fixed effect estimators. Using a panel of 19 OECD countries in the period 1980-'91, Magnani (2000) finds that higher inequality reduces environmental care, as predicted by the theoretical model set forth in the paper. The impact of inequality on environmental care, however, is statistically significant at 5% level in the pooled ordinary least squares model only.[12]

Marsiliani and Renström (2000) perform a similar analysis to test the inequality impact on environmental protection. Using two panels of 7 and 10 industrialized countries and regressing carbon intensity on income and inequality, they find that higher inequality increases emissions intensity (and thus lowers environmental protection) in a simple ordinary least squares model. In the fixed-effect specification, however, the inequality coefficient has the opposite sign and is not statistically significant with the larger panel.

Among the empirical studies that examine the impact of inequality on the environment, Ravallion et al. (2000) is the only one that takes CO_2 emissions as dependent variable. Using a panel of 42 countries in the period 1975-92, the authors first estimate CO_2 emissions as a cubic function of average per capita income ($\overline{Y}$) and of population and time trend (t). They find that the model in logs performs better than that in levels and that adding country dummy variables makes the cubic income term not statistically significant. For this reason, they limit their subsequent analysis to a log quadratic model and postulate that all parameters in the relationship are a function of inequality. This yields the following econometric model:

$$\ln (CO_2)_{it} = \beta_{1i} \ln \overline{Y}_{it} + \beta_{2i} \left(\ln \overline{Y}_{it}\right)^2 + \beta_{3i} \ln POPULATION_{it} + \beta_{4i} t + \eta_i + \varepsilon_{it}$$

where each parameter is:

$$\beta_{ki} = \beta_{k0} + \beta_{k1} GINI_i \ (k = 1, .., 4)$$

and the country fixed effect η is:

$$\eta_i = \eta_0 + \eta_1 GINI_i + \nu_i.$$

Ravallion et al. (2000) estimate the above equation in two ways: as a fixed-effect model and as a simple pooled model using ordinary least squares. The two regressions give quite different results and the authors argue that the pooled

[12] When the model is estimated without the interaction term $\beta_4(Y_{it} * r_{it})$, the inequality coefficient β_3 is negative in the three estimated models, but is not statistically significant in any of them (Magnani 2000, p.440, table 2).

model seems to be more reliable.[13] In this case, they find that higher inequality within countries reduces carbon emissions (i.e. $\frac{\partial \ln(CO_2)_{it}}{\partial GINI_i} < 0$). However, the impact of inequality on the environment decreases at higher average incomes (i.e. $\frac{\partial \ln(CO_2)_{it}/\partial GINI_i}{\partial \overline{Y}_{it}} < 0$). On the contrary, the income elasticity of CO_2 emissions ($\frac{\partial \ln(CO_2)_{it}}{\partial \ln \overline{Y}_{it}}$) turns out to be positive and is an increasing function of the Gini index. A greater inequality within countries, therefore, reduces CO_2 emissions, but increases their response to income growth. Finally, simulating redistribution from the richest to the poorest countries in the sample, Ravallion et al. (2000) find that the elasticity of emissions to redistribution is about 0.5. Therefore, they conclude that higher inequality, both within and across countries, lowers CO_2 emissions.

The above contributions represent the benchmark for the new evidence that we present below. In particular, we will often refer to Ravallion et al. (2000) since we also take CO_2 emissions as environmental indicator. As mentioned above, this study as well as the others examined in this paragraph use a pooled ordinary least squares model as preferred specification to investigate the impact of inequality on the environment. The aim of the present work is to show that the results obtained in the literature may heavily depend on the chosen specification and verify how these results change if we adopt a fixed-effect model that, in our opinion, provides a better description of reality in the present context.

3. Description of the data

In the absence of a single measure of environmental quality, many indicators have been used in the literature as proxy for environmental degradation (see, for instance, Borghesi, 1999). The present analysis focuses attention on carbon dioxide (CO_2) per capita emissions (metric tons per capita) as environmental indicator for two reasons: first, because carbon dioxide contributes to global warming more than any other greenhouse gas, second because data on carbon dioxide emissions are available for longer time-series than any other pollution indicator. The data source used for this variable is the US Oak Ridge National Laboratory (ORNL) at the Carbon Dioxide Information Analysis Center (CDIAC). ORNL provides estimates of national carbon emissions from fossil fuel consumption and cement

[13] Ravallion et al. (2000, p.21-22) claim that the results obtained with the ordinary least squares model seem more plausible than those of the fixed effect model and that the fixed effect estimators could be biased due to time-varying measurement errors.

manufacture. Data on fossil fuel consumption are based on the World Energy Data Set maintained by the United Nations Statistical Division. This data set concerns solid, liquid and gaseous fuels (primarily coals, petroleum products and natural gas, respectively). Data on cement manufacturing come from the Cement Manufacturing Data Set provided by the U.S. Geological Survey. ORNL annually calculates emissions of CO_2 by multiplying fuel consumption by the average carbon content of each fuel type, and cement production by the average carbon dioxide released during production (Marland and Rotty, 1984).[14]

The ORNL data set has two main limitations. In the first place, estimates of CO_2 emissions may depart from actual emissions.[15] In the second place, the data set does not consider some important emission sources such as deforestation and land-use changes, which account for 17-23% of total anthropogenic emissions (World Resources Institute, 1996). However, the ORNL data set is generally used in the literature and widely recognized as one of the best available sources for CO_2 emissions since they are calculated using a uniform estimation method from a single, harmonized data set available for all countries.[16]

As to the explanatory variables, all regressors used in our models (per capita gross domestic product, population density and industry value added) but inequality come from the World Bank, World Development Indicators. Per capita gross domestic product (GDP) is expressed in constant 1987 international dollars using Purchasing Power Parity (PPP). As Ravallion et al. (2000, p.15) point out, "GDP according to PPP has the advantage of expressing income in comparable units in terms of living standards across countries (as compared to GDP by market exchange rates)".[17] Population density is given by the number of people per

[14] CDIAC computes also CO_2 emissions from gas flaring, that is, the declining practice of burning off gas released during the extraction of petroleum (World Resources Institute, 1998, p.348). CO_2 emissions from gas flaring and cement manufacturing are about 3% of emissions from fossil fuel combustion (World Resources Institute 1998, p.349).

[15] Experts claim that "although estimates of world emissions are probably within 10% of actual emissions, individual countries estimates may depart more severely from reality" (World Resources Institute, 1998, p.348).

[16] Galeotti and Lanza (1999*a* and 1999*b*) are the only studies on CO_2 emissions that use an alternative data set recently developed by the International Energy Agency. This data set differs from the one used here in two respects: first, it does not include cement production and gas flaring, second, it uses a specific emission coefficient for each fossil fuel.

[17] Other authors prefer to use GDP based on exchange rate rather than on PPP since the former "better captures a country's control over the world product and its power in trade networks" (Roberts and Grimes, 1997, p.192). However, using GDP according to PPP makes our results comparable with those obtained by Ravallion et al. (2000).

square kilometer, whereas industry value added is expressed as percent of total GDP.

Data on inequality come from Deininger and Squire (1996). The authors have computed Gini coefficients and quintile shares for a large panel of countries, reporting whether inequality refers to individuals or households and whether is computed for income or expenditures. The Deininger and Squire data set is widely recognized as the most complete and updated database of inequality currently available. However, it presents international and intertemporal comparability problems because of definitional differences across countries and over time. For instance, some countries compute the Gini index based on consumption inequality, whereas others take income inequality. The former is generally lower than the latter since income has a greater variability than expenditures: Deininger and Squire (1996) find that the mean difference between income-based and expenditure-based Gini coefficients is about 6.6. To overcome this drawback, the authors scale up consumption inequality adding 6.6 to the expenditure-based Gini coefficients in the sample.

One important feature of the work by Deininger and Squire is that the authors indicated the quality of the assembled data and the underlying criteria. We used this indication to select only countries having high-quality data. More precisely, we restricted to the countries that have multiple high-quality observations on the Gini index in the period 1988-1995. This criterion differs from the one adopted by Ravallion et al. (2000, p.15) who compute "the average Gini index for each country, averaged over all the data available for that country from the high-quality sub-set of data". This means that the authors have a single value of inequality for each country, whereas here we have multiple observations for each nation in the sample.Although inequality differs more across countries than within countries over time, this feature is common to all other explanatory variables and we believe that treating inequality as constant may neglect part of the information. Some countries, in fact, show important changes in the level of inequality during the period that we examined.[18]

The results that will be presented below are based on two sets of data, depending on whether inequality is included among the explanatory variables. First, the environment-income relationship is examined using a panel of 126 countries

[18] In Bulgaria, for instance, inequality increased from 21.9 in 1988 to 34.4 in 1993. Several other countries (e.g. Hungary, Poland, Uganda, Venezuela, Zambia) experienced an increase by 8% or more in the same period.

in the period 1988-1995.[19] Table 1 shows the summary statistics for this sample. Then, inequality is introduced as additional explanatory variable to investigate its impact on CO_2 emissions and the CO_2-income relationship. Given the lack of high-quality data on inequality as measured by Deininger and Squire, this drastically reduces the number of countries for which all variables are available, leading to a sample of 37 countries in the same period (table 2). However, this second sample can be considered quite representative of the large income range existing across countries since it is composed of 11 low-income, 13 middle-income and 13 high-income countries.[20]

4. Analysis of the CO_2-GDP relationship

Most papers in the EKC literature assume that environmental degradation is a polynomial function of per capita income. The studies generally differ in three respects: (i) the choice between linear and log-linear models, (ii) the degree attributed to per capita income in the polynomial equation and (iii) the specification used by the authors (e.g. pooled ordinary least squares, fixed effects, random effects). As far as the first issue is concerned, both linear and log-linear models have advantages and disadvantages for the analysis of the EKC relationship.[21] Although both models were examined in this work, we preferred to focus attention mainly on the linear one since its coefficients can generally provide an immediate idea of the shape of the environment-income relationship.[22] As we will show below, however, all results obtained with the linear model are robust also to

[19] We examined the environment-income relationship in a basic model (where GDP is the only explanatory variable) and in a richer specification (where population density and industrial share of GDP are also introduced among the regressors). In the latter case the number of observations falls, leading to a balanced panel of 120 countries for a total of 850 data.

[20] Countries are divided by income levels according to the classification adopted by the World Bank (1998). The countries in question are: Australia, Bahamas, Bangladesh, Bulgaria, Canada, Chile, China, Colombia, Cote d'Ivoire, Dominican Republic, Ghana, Honduras, Hungary, India, Indonesia, Italy, Jamaica, Japan, Mauritania, Mexico, Netherlands, New Zealand, Nigeria, Pakistan, Philippines, Poland, Portugal, Romania, Singapore, Spain, Sweden, Thailandia, Uganda, UK, Usa, Venezuela, Zambia.

[21] See Galeotti and Lanza (1999*a*) for a extensive discussion of implications of the two models when applied to the environment-income relationship.

[22] Unlike the linear specification, the log-linear model provides no closed form analytical expression for the income turning point and "it is not possible to predict a priori the behavior of the function on the basis of the parameter signs, thus limiting their interpretability" (Galeotti and Lanza, 1999*a*, p.10).

the log-linear specification.

As to the choice of the functional form, most studies estimate environmental degradation as quadratic function of per capita GDP. However, several papers (e.g. Grossman and Krueger, 1994, Shafik 1994, Grossman, 1995, Torras and Boyce, 1998) have found that for some ecological indicators the environment-income relationship may be better described by a cubic function: environmental degradation first increases, then decreases and finally rises again. To make the present study comparable with the others, we estimated three regression models: 1) linear, 2) quadratic and 3) cubic in per capita GDP. Each functional form was estimated by least squares with and without country- and time-specific effects.[23] In what follows we will call pooled ordinary least squares (OLS) model the specification that does not take country- and time-specific effects into account. When specific effects were included in the model, we examined both fixed effects (FE) and random effects (RE) specifications. In our opinion, despite the waste of "between countries" information, the FE model is preferable to the RE model in the present context for two reasons. First, the RE model is generally adopted when one has time invariant explanatory factors since their effects on the dependent variable cannot be estimated using deviations from individual specific means as in the case of the FE within estimator. However, this drawback of the FE within estimator does not affect the estimations presented here since we will always use time varying regressors to explain CO_2 emissions. Second, the RE model assumes that individual specific effects are not correlated with the explanatory variables. This is equivalent to assuming that country effects such as resource endowments, efficiency of the monitoring systems, number of power plants and environmental policies adopted in the country are orthogonal to the country's per capita income, which seems rather unrealistic. Our a priori preference for the FE model was confirmed by the Hausman test that rejected the null hypothesis (i.e. that individual specific effects are orthogonal to the regressors) in all functional forms. The estimation results below, therefore, will present the FE but not the RE specification of the model.[24]

The result of the Hausman test mentioned above leads us to believe that the

[23] Although many authors (e.g. Shafik, 1994, Ravallion et al., 2000) introduce a time trend as proxy for technical progress, we prefer to use time dummies since they represent a non parametric form of the time trend, thus allowing for a less restrictive pattern than the linear trend.

[24] The choice of the FE model seems to reflect the approach prevailing in the EKC literature. In fact, only few studies (Selden and Song, 1994, Holtz-Eakin and Selden 1995, Vincent, 1997) examine also the random effects specification.

FE model is also more appropriate than the pooled OLS model. The latter, in fact, is just a special case of the RE specification which corresponds to a Generalized Least Squares (GLS). To further verify the FE model against the pooled OLS one, we performed an F-test on the country- and time-specific effects in a Least Squares Dummy Variable (LSDV) model.[25] The pooled OLS model, in fact, is equivalent to a LSDV model where all country- and time-effects are jointly equal to zero. The F-test rejected the null hypothesis that specific effects are jointly zero at 1% significance level in all estimated models. Therefore, since country-specific effects exist and are correlated with per capita income, pooled OLS estimates turn out to be biased and inconsistent (see, among the others, Hsiao, 1986). For this reason - differently from Ravallion et al. (2000) - we prefer a FE approach to the cross-country pooled OLS model generally used in the first studies (e.g. Panayotou, 1993, Shafik, 1994, Roberts and Grimes, 1997). In what follows, however, we will present the results obtained with both the FE and the pooled OLS model in order to compare our findings with those of the existing literature and show how results change as we pass from one specification to the other.

We started by examining the relationship between per capita CO_2 and per capita GDP, when inequality is not taken into account. Figure 8.1 is the scatter diagram of the CO_2-income relationship at different income levels, obtained by dividing observations by income groups and then plotting average CO_2 over average income for each group.

Following the standard approach in the EKC literature, we included population density ($DENS$) and industrial share of GDP (IND) among the explanatory variables.[26] Population density is generally believed to have a positive impact on environmental degradation. In fact, the higher the population density in a certain area, the higher human pressure on the environmental resources available in that area. Moreover, high population density is often associated with high emissions due to traffic congestion. However, some authors (Scruggs, 1998, p.270) argue that population density could also have a negative coefficient since higher density implies higher concern for environmental problems and thus lower emissions.

The industrial value added as percent of national income captures the so-called

[25] As it is well known, the FE within estimators of β parameters coincide with the LSDV ones.

[26] We also examined the simple relationship between per capita CO_2 and per capita GDP, with no further regressors taken into account. In this case, the FE model finds an EKC with turning point falling outside the range of income in the sample. This is consistent with the results obtained by the authors that examined carbon dioxide emissions in the literature (e.g. Cole et al., 1997, Holtz-Eakin and Selden, 1995). We omit this basic regression model for space constraints. Results, however, are available from the author upon request.

"composition effect" of income growth, namely how environmental degradation is affected by sector shifts in the composition of the economy taking place during the growth process. In general, we expect this variable to have a positive sign: since GDP is generally increasing over time, the higher the industrial share of GDP, the larger the industrial sector and the higher the emissions level.[27] However, this effect can be counterbalanced by the reduction in emission intensity as the industrial output shifts from heavy to less polluting industries with income growth. The overall sign of the industrial share of GDP, therefore, is a priori ambiguous.

In the case of the cubic functional form, the pooled OLS and FE regression models can be written as follows, respectively (**MODEL 1**):

$$\begin{aligned}(CO_2)_{it} &= \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \\ &+\beta_4 DENS_{it} + \beta_5 IND_{it} + \varepsilon_{it}\end{aligned} \tag{4.1}$$

$$\begin{aligned}(CO_2)_{it} &= \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \\ &+\beta_4 DENS_{it} + \beta_5 IND_{it} + \mu_i + \lambda_t + \varepsilon_{it}\end{aligned} \tag{4.2}$$

where μ_i measures the country fixed effect $(i = 1, ...N)$ and λ_t the time fixed effect $(t = 1, ...T)$.[28]

Table 3 presents the results obtained in this case with each functional form. Both pooled OLS and FE models find that the industrial value added has a statistically significant impact on CO_2 emissions: the higher the industrial share of GDP, the higher the CO_2 emission level. On the contrary, the pooled OLS and FE models achieve opposite results about population density: the former finds a negative coefficient for population density, whereas the latter detects a positive sign (i.e. higher density raises CO_2 emissions).[29] However, only the FE estimation is statistically different from zero. The pooled OLS and FE models achieve different conclusions also on the shape of the CO_2-GDP relationship.

[27] Taking sulphur dioxide emissions as environmental indicator, Panayotou (1997, p.472) argues that the industry share is "expected to enter with a positive sign since it is correlated with energy use, the main source of SO_2 emissions".

[28] Obviously, it will be $\beta_3 = 0$ in the quadratic model and $\beta_2 = \beta_3 = 0$ in the linear specification.

[29] The same occurred when we repeated the estimations of the two models eliminating industry value added.

The pooled OLS model finds a quadratic convex relationship between per capita carbon dioxide and per capita income, while the preferred specification with the FE model is a cubic one (see figure 8.2).[30]

Similar results apply if we adopt the log-linear model. As table 4 shows, the industry value added term is positive and statistically different from zero in both FE and pooled OLS models, whereas the CO_2-GDP relationship differs according to the chosen specification. In particular, the FE model finds a cubic relationship, while estimations of the pooled OLS model lead to an EKC with both CO_2 and GDP in logs.

5. The impact of inequality on CO_2 emissions and the CO_2-GDP link

Let us now examine how inequality affects CO_2 emissions and the CO_2-income relationship. When inequality is introduced in the model, the number of countries with multiple Gini observations in the period 1988-95 falls dramatically from 126 to 37. This reduces the number of available observations to 112. Figure 8.3 plots average Gini on average income for each country in this reduced sample. As the figure shows, poor countries have a wide range of inequality levels, whereas inequality seems to fall as income grows above a certain level.[31] Figure 8.4 shows that CO_2 emissions tend to decrease slightly as inequality grows. We repeated the analysis presented in the previous section introducing inequality as further explanatory variable. Adding the Gini index as regressor in (4.1) and (4.2), the pooled OLS and FE cubic models are respectively (**MODEL 2**):

$$\begin{aligned}(CO_2)_{it} &= \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \\ &\quad + \beta_4 DENS_{it} + \beta_5 IND_{it} + \beta_6 GINI_{it} + \varepsilon_{it}\end{aligned} \tag{5.1}$$

$$\begin{aligned}(CO_2)_{it} &= \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \\ &\quad + \beta_4 DENS_{it} + \beta_5 IND_{it} + \beta_6 GINI_{it} + \mu_i + \lambda_t + \varepsilon_{it}\end{aligned} \tag{5.2}$$

[30] To select the preferred specification we started from the richest functional form, i.e. the highest degree polynomial, and reduced progressively the model according to the statistical significance of the parameters. Thus, the cubic model is the preferred specification if β_3 is statistically significant at 5% level. If not, we move to the lower degree (quadratic) polynomial and look at the t-value of β_2, and so on.

[31] The correlation coefficient between the Gini index and per capita GDP is -0.14 in the panel.

Table 5 summarizes the correspondent estimation results. Comparison of tables 3 and 5 shows that the shape of the CO_2-income relationship has changed with respect to model 1. Based on the selection criterion described above, the FE model 2 finds that CO_2 is no longer a cubic, but a linear function of per capita income. As a further check, we also performed an F-test on the joint restriction that $\beta_2 = \beta_3 = 0$ in (5.2) and found that the null hypothesis is not rejected at 5% significance level. The results of the pooled OLS model are also substantially modified, passing from a quadratic convex CO_2-income curve in model 1 to evidence of a cubic relationship in model 2 (compare figures 8.2 and 8.5). The change in the CO_2-GDP relationship, however, does not depend on the introduction of inequality as additional regressor but on the use of a smaller sample when estimating model 2. In fact, using the same data set (sample 2) to compare results with and without inequality, we find that the shape of the CO_2-GDP relationship does not change with the introduction of inequality (i.e., from model 1 to model 2) neither in the pooled OLS nor in the FE specification.[32]

As to the impact of industry on carbon dioxide emissions, the industrial share of GDP has a positive and statistically significant coefficient β_5 both in the pooled OLS and in the FE model, like in model 1.[33] Population density has also a positive impact in both models. Its coefficient β_4, however, is not statistically significant in the FE specification, while is statistically different from zero in the preferred (cubic) specification of the pooled OLS model.

What about the impact of inequality on CO_2 emissions? In this regard, the two models achieve opposite results. The Gini coefficient, in fact, is positive but has a very low t-value in the FE model, whereas is negative and statistically significant in the pooled OLS model. The answer to question (ii), therefore, depends on the chosen specification: *an increase in inequality lowers CO_2 emissions according to the pooled OLS model, whereas it does not have a significant impact on CO_2 emissions according to the FE model.* It could be argued that the high standard error of the Gini coefficient might be determined by the existence of multicollinearity in the model. Population density, in fact, is almost constant within countries (see the last column of tables 1 and 2). The results of model 2, however, were unchanged when we repeated estimations eliminating population density from equations (5.1) and (5.2), which suggests that the low t-value of β_6 does not depend on the variability of population density within countries.

We also tested whether the results of table 5 are robust to the log-linear

[32] Results are available from the author upon request.

[33] We obviously refer to the preferred (linear) specification of the FE model.

specification. As table 6 shows, the impact of inequality on CO_2 emissions is basically unchanged even if the variables are expressed in logs rather than in levels. In particular, the Gini coefficient is positive but non statistically significant in the FE model, while the opposite holds in the pooled OLS model.

We then examined whether the same results apply with a different inequality measure. In fact, although the Gini coefficient is the most commonly used measure of inequality, it also presents some drawbacks. In particular, like any aggregate measure of inequality, the Gini coefficient is not sensitive to changes in the underlying income distribution: transferring a given amount from the top to the middle class has the same effect on the Gini index of a progressive transfer at the lower end of the distribution. To overcome this drawback, Deininger and Squire (1996, p.567) report also the income shares of population quintiles wherever possible. We then replaced the Gini coefficient with the following measure:

$INEQUALITY = (1 - Q_4) - Q_1$

where

Q_i = i-th quintile ($i = 1, 2, 3, 4$)

This variable - that we defined "interquintile difference" - measures the difference in the income shares between top and bottom quintiles of the population. Hence, while the Gini coefficient is a measure of the concentration of inequality within a country, the interquintile difference measures its extension. Replacing Gini with interquintile difference does not affect the results, which suggests that our findings are robust to a different inequality measure. The two variables, in fact, are highly correlated in the sample (correlation coefficient = 0.98).[34]

Since the results are little affected by the selected inequality measure, we decided to keep on using the Gini index for two reasons. First, Deininger and Squire provides a higher number of observations on the Gini coefficient than on the quintiles (see table 2). Second, the Gini index is a more complete measure of inequality than the quintiles since it is based on the whole income distribution, whereas the quintiles lose part of the information (e.g. the interquintile difference considers only the tails of the distribution).

Finally, taking the simple regression of CO_2 emissions on the Gini index as initial benchmark, we examined how the Gini parameter changes as further regressors are introduced in the model (see table 7). Two main results emerge

[34] Scruggs (1998) uses an alternative inequality measure to test the results obtained with the Gini index, namely the 80/20 income ratio: $\frac{Q_4}{Q_1}$. The correlation coefficient between Gini index and the 80/20 income ratio is 0.75 in our sample. Similarly to Scruggs, we find that no major changes occur in the results replacing the Gini index with $\frac{Q_4}{Q_1}$.

from this analysis. In the first place, consistently with model 2, all pooled OLS specifications find that the Gini coefficient is statistically significant, whereas all FE models that include other regressors beyond the Gini index conclude that inequality has no explanatory power. In the second place, the Gini coefficient keeps growing as subsequent regressors are included in the model.[35] A possible explanation for this trend is that estimations are downward biased in the initial specifications due to the omission of important explanatory variables. In fact, results suggest the existence of an omitted variable problem as we pass from one model to the subsequent, more complex specification by including an additional regressor.[36]

The estimation results of model 2 presented in this section might be affected by the presence of heterogeneity in the panel. The inequality impact on CO_2 emissions, for instance, might have opposite signs in rich and poor countries that tend to counterbalance in the panel, which could explain why the Gini coefficient β_6 turns out to be statistically non significant in the FE model. To investigate this problem more deeply, in the next paragraph we first examine the inequality impact for the subsamples of high- and low-income countries and then introduce a slight modification to the models (5.1) and (5.2).

5.1. Differential impact of inequality in rich and poor countries

To verify whether inequality has a different effect on CO_2 emissions in rich and poor countries, we repeated the analysis of model 2 for the sets of high- and low-income nations belonging to the data set that we used. As table 8 shows, the results of subsample analysis suggest that according to the FE model a rise in inequality generally increases emissions in poor countries and decreases them in rich ones, while the opposite result occurs with the pooled OLS model. Observe that the impact of inequality on CO_2 emissions turns out to be higher in rich than in poor countries as opposed to the result obtained by Torras and Boyce (1998) with other environmental indicators. The Gini coefficient, however, is still not statistically significant in the FE model, (whereas it is in the pooled OLS model for poor countries).

[35] The only exception concerns the introduction of population density in the model. In this case, β_6 is either constant or very close to its estimated value in the model without population density (compare rows 3 and 4 in Table 7). This seems to confirm that population density is statistically non significant, as suggested by the FE estimations.

[36] Results are available from the author upon request.

This analysis, however, suffers from a substantial loss of degrees of freedom since we split the sample used in model 2 into two subsamples. For this reason, we decided to adopt also an alternative approach to verify the differential impact of inequality in rich and poor countries by introducing a non linearity in model 2, as done by Barro (1999) in a recent contribution. To examine whether inequality affects growth differently in rich and poor countries, Barro (1999) allows the effect of the Gini index on economic growth to depend on the country's income level. For this purpose, he enters the Gini coefficient both linearly and as a product with (log of) per capita GDP among the regressors. Following Barro's approach, we allowed the impact of inequality on emissions to depend on the country's GDP by introducing the product of the Gini index with per capita GDP in models (5.1) and (5.2). The cubic pooled OLS and FE models will now look respectively as follows (**MODEL 3**):

$$\begin{aligned}(CO_2)_{it} &= \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \beta_4 DENS_{it} + \\ &\quad \beta_5 IND_{it} + \beta_6 GINI_{it} + \beta_7 GINI_{it} * GDP_{it} + \varepsilon_{it}\end{aligned} \tag{5.3}$$

$$\begin{aligned}(CO_2)_{it} &= \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \beta_4 DENS_{it} + \\ &\quad +\beta_5 IND_{it} + \beta_6 GINI_{it} + \beta_7 GINI_{it} * GDP_{it} + \mu_i + \lambda_t + \varepsilon_{it}\end{aligned} \tag{5.4}$$

The parameter β_6 measures the direct effect of inequality on CO_2 emissions, whereas β_7, the interaction term, measures its indirect effect through growth.

Observe that the impact of inequality on CO_2 emissions now changes at different income levels since it is:
$\frac{\partial (CO_2)_{it}}{\partial GINI} = \beta_6 + \beta_7 GDP$

As table 9 shows, estimation results of model 3 are consistent with those obtained from the subsample analysis above. In particular, the pooled OLS and FE models achieve again opposite results. According to the pooled OLS model, $\widehat{\beta}_6 < 0$ and $\widehat{\beta}_7 > 0$, therefore:
$\frac{\partial (CO_2)_{it}}{\partial GINI} \gtreqless 0$ when $GDP \gtreqless -\frac{\widehat{\beta}_6}{\widehat{\beta}_7}$

Viceversa, the FE specification finds that $\widehat{\beta}_6 > 0$ and $\widehat{\beta}_7 < 0$, therefore:
$\frac{\partial (CO_2)_{it}}{\partial GINI} \gtreqless 0$ when $GDP \lesseqgtr -\frac{\widehat{\beta}_6}{\widehat{\beta}_7}$.

In other words, the FE model finds that inequality increases CO_2 emissions in relatively poor countries (i.e. below certain income level), whereas it reduces emissions in relatively rich countries (i.e. above a threshold level). The opposite is true in the pooled OLS model. Table 9 shows the threshold income level above which the impact of inequality on CO_2 emissions is reversed. Consider, for instance, the cubic specification: the pooled OLS model suggests that greater inequality increases emissions when GDP is above 12.18 thousand dollars, whereas the FE model finds that this occurs when GDP is below 11.55 thousand dollars.

We should be very cautious, however, in drawing any conclusion on the existence of a differential impact of inequality. Consistently with model 2, in fact, β_6 and β_7 are statistically significant in the pooled OLS model, but FE estimations of these coefficients are not statistically different from zero in all estimated functional forms. This seems to suggest, therefore, that inequality has indeed no explanatory power for CO_2 emissions and that the low t-value observed for the Gini parameter in model 2 is not the result of the aggregation of countries with opposite inequality impacts.

The difference between the pooled OLS and FE models concerns also the significance of the other explanatory variables. In the cubic specification, the pooled OLS model finds that the impact on CO_2 emissions is significantly different from zero for all explanatory variables, which also implies a cubic relationship between CO_2 and per capita income. On the contrary, FE estimations detect a linear CO_2-GDP relationship like in model 2. Also observe that the industrial share of GDP is the only other variable beyond GDP that is statistically different from zero in the preferred linear specification of the FE model. This seems to suggest that the bulk of the variations in the carbon dioxide emissions depends on unobservable country specific effects. Similar results apply if we estimate a semilogarithmic specification by replacing the product term $GINI_{it} * GDP_{it}$ with $GINI_{it} * \log GDP_{it}$ in (5.3) and (5.4).

Finally, following the approach adopted in the previous sections, we tested the robustness of our results by estimating model 3 with all variables in logs. As table 10 shows, results are basically unchanged, namely, the pooled OLS and FE model achieve opposite conclusions on the sign and statistical significance of β_6 and β_7, and thus also on the differential inequality impact in rich and poor countries. Once more, the FE estimations of β_6 and β_7 are not statistically different from zero in all estimated functional forms.

6. Conclusions

This study explored the link between environmental degradation, economic growth and income inequality within the framework of the environmental Kuznets curve (EKC) literature. To investigate this issue, we first examined the relationship between carbon dioxide emissions and per capita income when inequality is not taken into account and then analyzed how inequality affects CO_2 emissions and their relationship with economic growth.

Despite the large and increasing number of contributions on the EKC, only very few studies have investigated the environmental impact of inequality. These studies have generally used pooled OLS models. Pooling observations, however, disregards the heterogeneity of the countries included in the panel. For this reason, the results obtained in the literature may heavily depend on the chosen specification and may change if we adopt a FE model. This model, in our opinion, provides a better description of reality in the present context, as confirmed also by the performed test that rejected the hypothesis underlying the pooled OLS model in all estimated specifications.

Our findings show that the pooled OLS and the FE models systematically achieve different or even opposite results. This is particularly evident for the impact of inequality on CO_2 emissions. If one adopts a pooled OLS model, in fact, the Gini coefficient turns out to be negative and statistically significant so that greater inequality reduces emissions. This is consistent with the result obtained by Ravallion et al. (2000), which is the only study currently available on the relationship between income distribution and carbon dioxide emissions. If we use a FE model, however, the inequality coefficient shifts from negative to positive as additional regressors are introduced in the model, but *inequality has always a statistically non significant impact on CO_2 emissions*. This outcome has two possible explanations: either income distribution has no necessary link with environmental degradation, as Scruggs (1998) argued, or the positive and negative impact of inequality on the environment tend to counterbalance. This could occur since poor people contribute less to pollution by consuming less than the rich (hence lower inequality reduces emissions), but they also use energy less efficiently than the latter (thus lower inequality increases emissions).

Finally, we set forth the hypothesis that the overall non significance of the Gini coefficient might depend on a differential impact of inequality for high- and low- income countries. To test whether this is the case, we performed a further analysis using a more complex specification. According to the FE model, a more unequal income distribution seems to increase emissions in poor countries and decrease them in rich ones. The Gini coefficient, however, is still not statistically different from zero in the FE model, therefore the lack of a significant inequality impact on CO_2 emissions seems independent of the aggregation of heterogeneous countries in the panel. Further investigation will be needed to examine this differential impact of inequality on environmental degradation. For this purpose, future research should examine the relationship between environment and inequality in single-country studies, comparing the outcomes in developed and developing countries to analyze whether such a relationship changes at different income levels. Future empirical work should also be devoted to investigate whether CO_2 emissions are affected by inequality across countries rather than within countries. Large and increasing disparities across countries, in fact, are likely to make international environmental policies more difficult to achieve and thus might influence the emission path of global pollutants like CO_2.

7. References

Barbier E., 1997, "Introduction to the environmental Kuznets curve special issue", Environment and Development Economics, vol.2, pp. 369-381, Cambridge University Press.

Barro R., 1999, "Inequality, growth and investment", NBER Working Paper n.7038, Cambridge, Massachusetts, USA.

Borghesi S., 1999, "The environmental Kuznets curve: a survey of the literature", Fondazione ENI Enrico Mattei, Nota di lavoro 85.99, Milan, Italy.

Boyce J.K., 1994, "Inequality as a cause of environmental degradation", Ecological Economics, vol.11, pp.169-178.

Cole M.A., Rayner A.J., Bates J.M., 1997, "The environmental Kuznets curve: an empirical analysis", Environment and Development Economics, vol.2, pp. 401-416, Cambridge University Press.

Galeotti M., Lanza A., 1999*a*, "Desperately seeking (environmental) Kuznets", Fondazione ENI Enrico Mattei, Nota di lavoro n.2.99, Milan, Italy.

Galeotti M., Lanza A., 1999*b*, "Richer and cleaner? A study on carbon dioxide emissions in developing countries", Energy Policy, vol.27 (10), pp.565-573, Elsevier Science Ltd.

Gastil R., 1989, "Freedom in the world, 1988-1989", Freedom House, New York.

Grossman G.M., Krueger A.B., 1994, "Economic growth and the environment", NBER Working Paper n.4634; also in Quarterly Journal of Economics Vol. 110 (1995), pp.353-377.

Grossman G.M., 1995, "Pollution and growth: what do we know?", in "The economics of sustainable development" edited by Goldin I. and Winters L.A., Cambridge University Press, pp.19-45.

Deininger K., Squire L., 1996, "A new data set measuring income inequality", The World Bank Economic Review, vol.10, n.3, pp.565-91, The World Bank, Washington D.C.

Holtz-Eakin D., Selden T.M., 1995, "Stoking the fires? CO_2 emissions and economic growth", Journal of Public Economics, n.57, pp.85-101.

Hsiao C., 1986, "Analysis of panel data", Cambridge University Press, Cambridge.

Kaufmann R.K., Davidsdottir B., Garnham S., Pauly P., 1998, "The determinants of atmospheric SO_2 concentrations: reconsidering the environmental Kuznets curve", Ecological Economics, Vol. 25, pp.209-220.

Kuznets S., 1955, "Economic growth and income inequality", American Economic Review, vol.45, pp.1-28.

Magnani E., 2000, "The environmental Kuznets curve, environmental protection policy and income distribution", Ecological Economics, vol.32, pp.431-443.

Marland G., Rotty R.M., 1984, "Carbon dioxide emissions from fossil fuels: a procedure for estimation and results for 1950-1982", Tellus, 36B, pp.232-261.

Marsiliani L., Renström T.I., 2000, "Inequality, environmental protection and growth", CentER working paper n.2000-34, Tilburg University, The Netherlands.

Panayotou T., 1993, "Empirical test and policy analysis of environmental degradation at different stages of economic development", World Employment Programme Research, Working Paper 238, International Labour Office, Geneva.

Panayotou T., 1997, "Demystifying the environmental Kuznets curve: turning a black box into a policy tool", Environment and Development Economics, vol.2, pp.465-484, Cambridge University Press.

Ravallion M., Heil M., Jalan J., 2000, "Carbon emissions and income inequality", Oxford Economic Papers, forthcoming; previously pubblished as "A less poor world, but a hotter one?", 1997, The poverty, environment and growth working paper series, working paper n.13, The World Bank, Washington D.C.

Roberts J.T., Grimes P.E., 1997, "Carbon intensity and economic development 1962-91: a brief exploration of the environmental Kuznets curve", World Development, vol.25, n.2, pp.191-198, Elsevier Science Ltd.

Scruggs L.A., 1998, “Political and economic inequality and the environment”, Ecological Economics, vol.26, pp.259-275.

Selden T.M., Song D., 1994, “Environmental quality and development: is there a Kuznets curve for air pollution emissions?”, Journal of Environmental Economics and Management, n.27, pp.147-162.

Shafik N., 1994, “Economic development and environmental quality: an econometric analysis”, Oxford Economic Papers, vol. 46, pp.757-773.

Suri V., Chapman D., 1998, “Economic growth, trade and energy: implications for the environmental Kuznets curve”, Ecological Economics, vol.25, pp.195-208.

Torras M., Boyce J.K., 1998, “Income, inequality and pollution: a reassessment of the environmental Kuznets curve”, Ecological Economics, vol.25, pp.147-160.

Unruh G.C., Moomaw W.R., 1998, “An alternative analysis of apparent EKC-type transitions”, Ecological Economics, vol.25, pp.221-229.

Vincent J.R., 1997, “Testing for environmental Kuznets curves within a developing country”, Environment and Development Economics, vol.2, pp.417-431, Cambridge University Press.

World Bank, 1998, “World Development Indicators 1998-1999”, Washington D.C.

World Resources Institute, 1996, “World Resources 1996-97: a guide to the global environment”, New York, Oxford University Press.

World Resources Institute, 1998, “World Resources 1998-99”.

8. Appendix

Table 1: summary statistics of sample 1 (126 countries in 1988-1995)[37]

VARIABLE	obs	mean	std.dev.	min	max	var.ratio
per capita CO_2 emissions (tons)	1008	4.42	6.49	0.01	49.38	19.54
per capita GDP	1007	5.69	5.66	0.30	24.03	11.88
POPULATION DENSITY	992	1.95	6.75	0.01	62.18	3.88
INDUSTRY value added (% GDP)	857	29.86	10.86	8.05	68.91	33.82

Table 2: summary statistics of sample 2 (37 countries in 1988-1995)[38]

VARIABLE	obs	mean	std.dev.	min	max	var.ratio
per capita CO_2 emissions (tons)	296	5.2	5.15	0.05	27.13	17.62
per capita GDP	296	6.82	5.91	0.62	21.07	8.56
POPULATION DENSITY	296	2.48	7.40	0.01	48.95	4.71
INDUSTRY value added (% GDP)	253	32.92	9.41	10.18	60.96	40.76
GINI	112	36.91	8.76	20.69	57.88	24.57
Interquintile difference (1-Q_4-Q_1)	97	36.06	8.98	18.11	59.3	26.28

[37] The original series of per capita GDP was divided by 1000 so that this variable has the same magnitude of the others and we can avoid scale problems. The last column measures the variability ratio that was computed as the standard deviation of each variable across countries divided by that within countries (expressed in percent terms).

[38] The Gini index is in percent, as reported in the original Deininger and Squire (1996) data set. Q_1 and Q_4 are the cumulative income shares of the first and fourth quintile, respectively. The measure of interquintile difference is multiplied by 100 to harmonize it with the magnitude of the other variables.

Table 3: model 1 with variables in levels[39]

	pooled OLS MODEL			FE MODEL		
	linear	**quadratic**	cubic	linear	quadratic	**cubic**
GDP	0.74 (30.75)	0.39 (4.42)	0.29 (1.64)	0.9 (18.71)	0.32 (2.02)	1.31 (4.31)
GDP^2		0.02 (3.98)	0.03 (1.48)		0.02 (3.83)	-0.08 (-3)
GDP^3			-0.0005 (-0.63)			0.003 (3.8)
$DENSITY$	-0.01 (-0.68)	-0.01 (-0.9)	-0.01 (-0.94)	0.38 (3.48)	0.3 (2.79)	0.29 (2.7)
$INDUSTRY$	0.12 (11.53)	0.14 (12.27)	0.14 (11.9)	0.02 (3.13)	0.03 (3.99)	0.02 (3.09)
intercept	-3.61 (-11.2)	-3.44 (-10.67)	-3.38 (-10.02)	-2.34 (-6.54)	-0.64 (-1.14)	-1.96 (-2.97)
adj.R^2	0.64	0.65	0.65	0.43	0.44	0.45

Table 4: model 1 with variables in logs

	pooled OLS MODEL			FE MODEL		
	linear	**quadratic**	cubic	linear	quadratic	**cubic**
$lnGDP$	1.27 (48.21)	1.46 (24.38)	1.45 (22.88)	0.56 (9.27)	0.4 (5.21)	0.41 (5.39)
$(lnGDP)^2$		-0.07 (-3.4)	-0.06 (-0.96)		0.09 (3.5)	0.21 (3.42)
$(lnGDP)^3$			-0.002 (-0.1)			-0.03 (-2.18)
$lnDNS$	0.01 (1.16)	0.02 (1.5)	0.02 (1.49)	-0.06 (-0.4)	0.006 (0.03)	0.004 (0.02)
$lnIND$	1.19 (16.8)	1.12 (15.28)	1.12 (14.98)	0.13 (2.77)	0.13 (2.89)	0.11 (2.5)
intercept	-5.25 (-21.8)	-5.06 (-20.58)	-5.06 (-20.46)	-0.62 (-0.98)	-0.96 (-1.51)	-1.01 (-1.58)
adj.R^2	0.84	0.84	0.84	0.18	0.19	0.20

[39] In this table as well as in the following ones t-statistics are indicated in brackets. For each model, the preferred specification is indicated in bold. Notice that the R^2 of the FE model is an R^2 within.

Table 5: model 2 with variables in levels

	pooled OLS MODEL			FE MODEL		
	linear	quadratic	**cubic**	**linear**	quadratic	cubic
GDP	0.72 (16.47)	0.2 (1.11)	2.33 (6.61)	0.93 (3.78)	1.7 (3.57)	2.33 (2.95)
GDP^2		0.02 (2.8)	-0.23 (-5.87)		-0.02 (-1.87)	-0.11 (-1.3)
GDP^3			0.008 (6.7)			0.002 (1.004)
$DENSITY$	0.03 (0.95)	0.05 (1.37)	0.11 (3.28)	0.51 (0.69)	0.49 (0.67)	0.62 (0.84)
$INDUSTRY$	0.1 (4.34)	0.13 (5.23)	0.07 (2.99)	0.07 (3.56)	0.04 (1.79)	0.04 (1.56)
$GINI$	-0.09 (-3.22)	-0.09 (-3.33)	-0.12 (-5.24)	0.01 (0.44)	0.01 (0.68)	0.01 (0.59)
intercept	0.58 (0.37)	0.68 (0.45)	0.81 (0.64)	-4.83 (-2.33)	-6.49 (-2.93)	-6.92 (-3.07)
adj.R^2	0.77	0.79	0.86	0.7	0.72	0.73

Table 6: model 2 with variables in logs

	pooled OLS MODEL			FE MODEL		
	linear	quadratic	**cubic**	linear	**quadratic**	cubic
$\ln GDP$	0.99 (21.36)	1.11 (6.99)	1.45 (6.55)	1.06 (3.97)	-0.07 (-0.16)	-0.52 (-0.74)
$(\ln GDP)^2$		-0.03 (-0.73)	-0.51 (-2.3)		0.54 (2.88)	0.91 (1.89)
$(\ln GDP)^3$			0.12 (2.19)			-0.08 (-0.84)
$\ln DNS$	-0.05 (-1.73)	-0.05 (-1.75)	-0.04 (-1.48)	-0.3 (-0.37)	-1.16 (-1.4)	-1.35 (-1.56)
$\ln IND$	1.66 (11.35)	1.59 (9.31)	1.61 (9.6)	0.26 (1.08)	0.27 (1.2)	0.29 (1.28)
$\ln GINI$	-0.98 (-4.92)	$-1.$ (-4.97)	-1.07 (-5.32)	0.03 (0.2)	0.06 (0.4)	0.09 (0.55)
intercept	-2.35 (-2.45)	-2.08 (-2.02)	-1.93 (-1.9)	-0.19 (-0.05)	3.52 (0.97)	4.28 (1.14)
adj.R^2	0.9	0.9	0.9	0.57	0.63	0.64

Table 7: values of the Gini parameter β_6 with additional explanatory variables.[40]

Explanatory variables	pooled OLS MODEL	FE MODEL
GINI	-0.19 (-3.81)	-0.08 (-2.53)
GINI, GDP	-0.14 (-6.2)	-0.01 (-0.4)
GINI, GDP, DENSITY	-0.14 (-6.66)	-0.009 (-0.33)
GINI, GDP, DENSITY, INDUSTRY V.A.	-0.12 (-5.24)	0.01 (0.59)

Table 8: estimates of Gini parameter in model 2 for high-income (H) and low-income (L) countries.[41]

	LINEAR		QUADRATIC		CUBIC	
	H	L	H	L	H	L
pooled OLS	0.17 (1.4)	-0.04 (-4.71)	0.14 (1.2)	-0.06 (-4.72)	0.14 (1.2)	-0.05 (-3.96)
FE	0.02 (0.45)	0.005 (0.92)	-0.007 (-0.11)	0.002 (0.5)	-0.015 (-0.09)	0.004 (0.7)

[40] T-values in parentheses. Note that the richer specification in the last row corresponds to model 2 examined above.

[41] The 13 high-income countries are: Australia, Bahamas, Canada, Italy, Japan, Netherlands, New Zealand, Portugal, Singapore, Spain, Sweden, UK, USA. The 11 low-income countries are: Bangladesh, China, Cote d'Ivoire, Ghana, Honduras, India, Mauritania, Nigeria, Pakistan, Uganda, Zambia. Income ranges between 8.4 and 21.07 thousand dollars for the former set of nations and between 0.6 and 2.3 thousand dollars for the latter.

Table 9: model 3 with variables in levels

	pooled OLS MODEL			FE MODEL		
	linear	quadratic	**cubic**	**linear**	quadratic	cubic
GDP	-0.54 (-1.86)	-0.82 (-2.65)	1.57 (3.02)	1.05 (3.03)	1.71 (3.41)	2.42 (2.84)
GDP^2		0.02 (2.29)	-0.2 (-4.78)		-0.02 (-1.78)	-0.11 (-1.32)
GDP^3			0.007 (5.38)			0.002 (1.03)
DNS	-0.001 (-0.02)	0.01 (0.38)	0.08 (2.37)	0.45 (0.6)	0.48 (0.65)	0.59 (0.43)
IND	0.11 (4.9)	0.13 (5.51)	0.07 (3.31)	0.07 (3.49)	0.04 (1.77)	0.04 (1.56)
Gini	-0.24 (-5.62)	-0.23 (-5.37)	-0.18 (-4.73)	0.02 (0.66)	0.01 (0.46)	0.02 (0.59)
Gini*GDP	0.03 (4.38)	0.03 (4.02)	0.01 (1.96)	-0.003 (-0.49)	-0.0003 (-0.05)	-0.002 (-0.28)
$\frac{\partial CO_2}{\partial GINI} > 0$	GDP>6.95	GDP>7.21	GDP>12.18	GDP<7.82	always	GDP<11.55
intercept	6.18 (3.2)	5.76 (3.03)	3.17 (1.83)	-5.24 (-2.33)	-6.52 (-2.81)	-7.12 (-2.98)
adj.R^2	0.81	0.82	0.86	0.7	0.72	0.73

Table 10: model 3 with variables in logs

	pooled OLS MODEL			FE MODEL		
	linear	quadratic	**cubic**	linear	**quadratic**	cubic
lnGDP	-2.97 (-3.22)	-2.86 (-3.02)	-2.56 (-2.75)	1.06 (1.28)	0.22 (0.26)	-0.22 (-0.22)
$(\text{lnGDP})^2$		-0.02 (-0.5)	-0.52 (-2.56)		0.55 (2.89)	0.93 (1.9)
$(\text{lnGDP})^3$			0.13 (2.51)			-0.08 (-0.84)
lnGini	-2.42 (-6.37)	-2.42 (-6.34)	-2.51 (-6.73)	0.03 (0.11)	0.18 (0.59)	0.21 (0.68)
lnGini$*$ $*$lnGDP	1.11 (4.31)	1.1 (4.24)	1.11 (4.43)	-10^{-5} (0)	-0.09 (-0.44)	-0.09 (-0.45)
$\frac{\partial \ln CO_2}{\partial \ln GINI}>0$	GDP>8.84	GDP>9.02	GDP>9.59	always	GDP<7.38	GDP<10.31
lnDNS	-0.09 (-2.83)	-0.09 (-2.83)	-0.08 (-2.57)	-0.3 (-0.34)	-1.33 (-1.45)	-1.52 (-1.6)
lnIND	1.78 (13.02)	1.74 (10.83)	1.76 (11.27)	0.26 (1.07)	0.28 (1.21)	0.3 (1.29)
intercept	2.51 (1.75)	2.65 (1.81)	2.87 (2.02)	-0.19 (-0.05)	3.83 (1.03)	4.61 (1.2)
adj.R^2	0.91	0.91	0.92	0.57	0.63	0.64

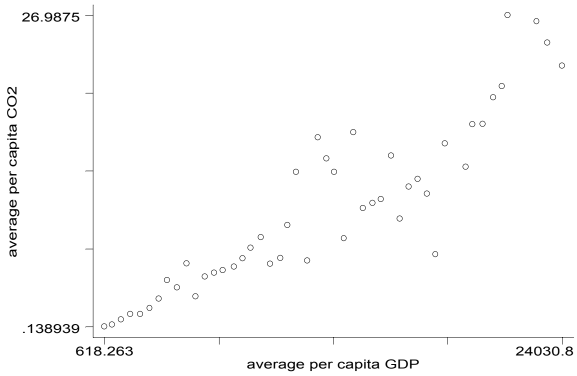

Figure 8.1: $CO_2 - GDP$ by income categories

Model 1: estimated CO_2-GDP relationship with FE model (solid line) and pooled OLS model (dotted line)

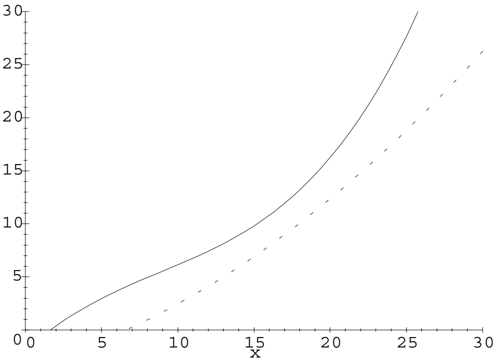

Figure 8.2:

Flex point in the cubic FE model: GDP=8.97, CO_2=5.03

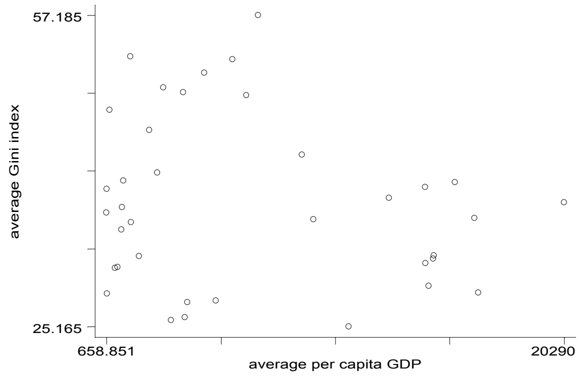

Figure 8.3: average Gini-GDP in sample 2

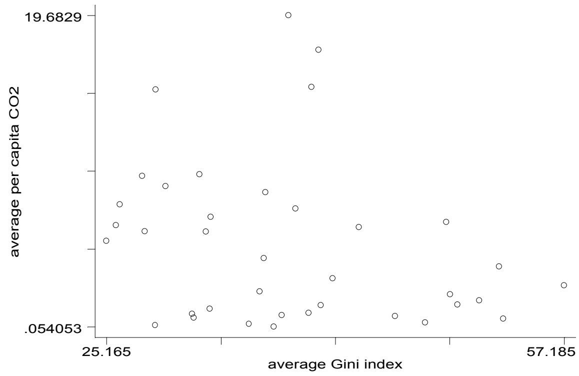

Figure 8.4: average CO_2-Gini in sample 2

Model 2: estimated CO_2-GDP relationship with FE model (solid line) and pooled OLS model (dotted line)

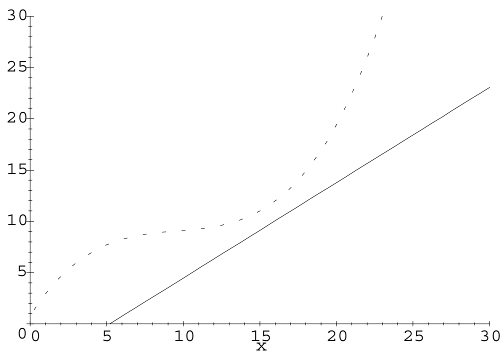

Figure 8.5:

Flex point in the cubic pooled OLS model: GDP=9.15, CO_2=8.77