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Is Democracy Good for the Environment?
Quasi-Experimental Evidence from Regime Transitions

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Abstract This paper tests the hypothesis that democratisation is conducive to less environmental depletion due to human activity. Using interrupted time series design for a panel of 47 transition countries and two indexes of pollution, CO_2 emissions and PM10 concentrations, I find that democracies and dictatorships have two different targets of environmental quality, with those of democracies higher than those of dictatorships. Income inequality may as well alter this targets, but with opposite effects in the two different regimes.

Keywords Democracy · Environment · Cointegration · Interrupted time series · Segmented regression

JEL Classification C23 · D31 · H23 · Q58 · Q51

1 Introduction

The relation between various measures of pollution and democracy is highly debated. Two different views about the effect of democracy on the environment have been put forward: a dominant thinking of the 1970s was that democracy and its associated liberties to pollute, consume and procreate would generate ecological catastrophes, and the inability of governments to control the "tragedy of the commons" is an evident example of such a failure of democracies in the management of environmental issues (Desai 1998; Hardin 1968). Democracy is also known to be a means for redistributing income and power to the poor, so to those whose consumption has an higher marginal impact on the environment; Rodrik (1999) for example, presents evidence that democracy is associated with an higher share of wages in GDP and thus lower Milanovic (2000) finds that democracies with greater inequality of factor income redistribute more in favour of the poorer.

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At present, however, there is a growing empirical research on the possible affinities between democracy and ecology. There are several reasons for such a positive relationship[1], basically: (1) democracies respect individual rights and so environmentalists are free to market their ideas and transform them into environmental legislation; (2) the necessity of democratic government to be elected (or reelected) makes them more responsive to their citizens; (3) open political systems are more likely to learn from scientists and other concerned citizens than are autocracies; (4) democratic states tend to cooperate with each other within international environmental agencies, and finally, (5) because democracies all have free market economies, business in the market can be subject both to environmental incentives and sanctions (Dasgupta and Mäler 1995; Schultz and Crockett 1990; Payne 1995). Furthermore, democracies respect human life more than autocracies and therefore they are more responsive to life-threatening environmental degradation (Gleditsch and Sverdrup 2003).

In the empirical literature, Bhattarai and Hammig (2001), for example, use a measure of institutional quality (measured by an index of political rights and civil liberties) to account for the role of different policy regimes in the causes of deforestation in Latin America, Africa and Asia. Torras and Boyce (1998) use a similar technique for a panel data survey of a variety of air and water pollution indicators. Gallagher and Thacker (2008) introduce a concept of "stock of democracy" to study its implications through time. They all find positive evidence that civil liberties and political rights are associated with more pro-environmental behaviour.

All these empirical contributions, however, are not immune from criticisms. In general, cross country studies fail to establish causation between regimes and various measures of pollution because of the positive correlation between income and democratic institutions (Barro 1996a, b, 1999; Przeworski and Limongi 1993) and between income and clean technologies (Hausman 1979). Empirical works which use composite indexes of civil liberties and political rights do not distinguish clearly democracies from other types of regimes. Regressions in panel data are usually done by assuming fixed effect models, which can solve the issue of accounting for time invariant heterogeneity, but when distinction between democracies and autocracies is done by using dummy variables, they do not disentangle the effects of democracy from other effects in play during periods of democracy. It is well known that other factors may influence the performance of a country. In the ideal situation, one could observe the same country simultaneously under two different types of regime, and this would guarantee that all the other variables are held constant. But since this is not feasible (what one can observe is the same country at different points in time), a simple regression, even if it is able to control for time invariant unobservables, could be biased due to the time variant unobservable variables. Several effects may cause this bias: *History*, such as events which occurred during the period considered providing an alternative explanation of a given phenomenon, *maturation*, or processes through which the country produces changes as a function of time per se (like for example the maturation of technology towards less energy intensive production processes) or even *instability*, referred at the fact that all time series are unstable even when no treatments are applied are all typical unobservable effects that may bias these estimates. The paper by Gallagher and Thacker (2008) partially solves the issue of the time-variant unobservables by introducing the concept of "stock of democracy" but they fail to check what is the effect of autocracy on the level of CO_2 emissions. Observing that democracy has a positive effect on the environment does not exclude a priori that dictatorship has not.

In this paper, I make use of interrupted time series (ITS) design to study the effect of democratisation on two indicators of air quality, CO_2 emissions and levels of PM10 con-

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[1] for a systematisation of the argument, see Payne (1995).

centration, in a panel of 47 transition countries during the period 1950–2002 (for CO_2) and 1990–2002 for PM10 concentrations.

The method of ITS is a powerful quasi-experimental approach for evaluating the effects of interventions or naturally occurring events. In the literature, it is traditionally proposed for single time series studies (Shadish et al. 2002; Campbell and Stanley 1966; Cook and Campbell 1979), and only recently it has been applied in panel data contexts. Allison (1994) develops several methods for using multiwave panel data to estimate the effects of interventions by synthesizing the literature on interrupted time series with econometric treatment of pooled time series, cross section data. Bloom (2003) uses ITS approach for studying how a school reform affects three indexes of student performance for different cohorts of students, Çíftçí (2005) examines the collective responses of the Europeans to different environments of integration by using multiple ITS design with panels of data, and Gao et al. (2007) use ITS analysis to study the impact of the introduction of critical care outreach services in 172 different critical care units in England between 1996 and 2004.

Combining ITS design and panels of data allows to take the advantages of both those tools: panel data estimation methods allow to control for unobservable country-specific effects that result in a missing-variable bias in cross-sectional studies. I included in my sample only transition countries because I believe it is a natural and transparent way to study the effect of democratisation. The inclusion of countries which have not shifted regime may bias the estimate due to the fact that other events (and not democracy) may be responsible for such a change (like, for instance, technological progress). This effect may be more easily disentangled in transition countries due to the possibility of running segmented regressions, as it will become clearer later.

Segmented regression analysis of ITS data allows us to assess, in statistical terms, how much an intervention changed an outcome of interest, immediately and over time, instantly or with delay, and whether factors other than the intervention could explain the change.

So, contrary to the other methods commonly used in the literature, this approach is suitable to measure the effect of democratisation through time, taking into account of other time-variant effects, and moreover, it is capable of identifying whether other factors (possibly unknown) are driving the results.

This paper is organised as follows: Sect. 2 motivates the paper, Sect. 3 describes the dataset used, Sect. 4 illustrates the estimation techniques and results, and Sect. 5 concludes.

2 Motivations

Does democracy really benefit environmental quality? Using a sample of 47 transition countries, I observe that during the period 1990–2002 the average concentration of PM10 recorded during spells of dictatorship is about 1.36 times bigger than the concentration recorded during democratic periods, despite the average level of GDP is 2.25 times bigger during democracy than during dictatorship spells[2].

The average intensity of CO_2 emissions produced per unit of GDP is 1.17 times larger in periods of dictatorship than in periods of democracy.[3] Several countries show clearly a decrease in the intensity of emission per unit of GDP in proximity to the regime shift:

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[2] The average concentration of PM10 during democracy is 69.67906 and during dictatorship is 89.14407. GDP during democratic periods is, on average, 117,648.9 against 52,189.88 during dictatorship.

[3] This average is computed over all the 53 years and over all the countries, conditioned to periods of democracy or dictatorship. The data for periods of democracy show an intensity of CO_2 emissions (in Kg of carbon) per unit of income of 0.1269 against 0.1485 during periods of dictatorship.
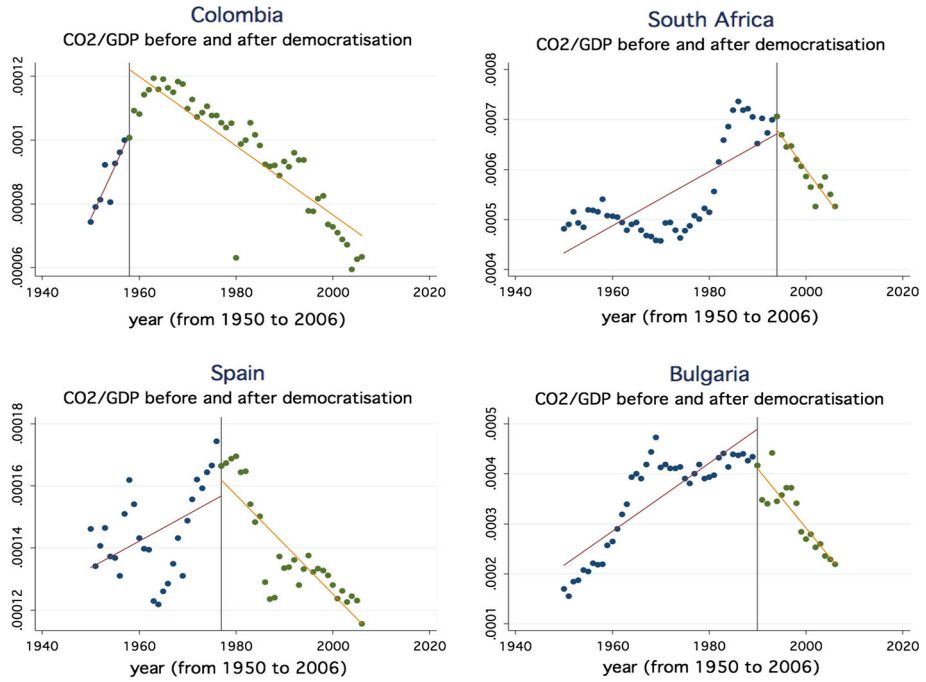
Fig. 1 CO_2 emissions (expressed in Kg of carbon) per \$1 of GDP before (*left*) and after (*right*) democratisation, represented by a vertical line, and their linear fits

Figure 1 shows, for Colombia, South Africa, Spain and Bulgaria, the actual (dotted) and fitted (line) levels of intensity of emissions (expressed in tons of carbon per unit of GDP). The vertical line in each subfigure represents the date of the regime shift. All the four countries have experienced a transition to democracy after long periods of dictatorship. After the regime shift we observe a reverse pattern for emissions; while before democratisation the tendency is to increase the intensity of CO_2 emissions in production, later we observe a decline, which is persistent through time.

Variations in percapita emissions are consistently reduced during democratic periods as the following simple fixed-effects regression that includes all the sample of 47 countries and 53 years shows (standard errors in parenthesis)[4]:

$$\Delta CO_{2it} = \underset{(1.89233)}{8.229862} + \underset{(0.0079892)}{0.1170303} \, \Delta GDP_{it} + \underset{(3.356346)}{-17.3097} \, Dem_{it}$$

with ΔCO_{2it} denoting predicted variations in the level of percapita CO_2 emissions expressed in Kg of carbon occurred between $t-1$ and t for country i, ΔGDP_{it} variations in the level of percapita income occurred between $t-1$ and t for country i, and Dem_{it} is a dummy variable coded 1 during periods of democracy, and 0 otherwise. All the estimated coefficients are significant at 1 % level.

As previously anticipated, variations in CO_2 emissions are consistently reduced during periods characterised by democratic institutions. The coefficient related to the variable Dem denotes exactly how the variation in the level of emissions decreases as a consequence of democratisation. In other words, it represents the average "kink" in the two fitted lines before and after the regime change, for the whole sample of countries.

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[4] All the results are also significant at 1 % level.

3 Data and Descriptive Statistics

I consider percapita CO_2 emissions and PM10 concentrations as dependent variables. Data on CO_2 are from Marland et al. (2008) and are available for the period 1950–2002. They refer to emissions from burning fossil fuels and manufacturing cement, expressed in Kg of carbon. Their estimates are based on energy data from the United Nations and cement data from the US Geological Survey (for an analytical description of the estimation procedures see Marland and Rotty 1984). Data for PM10's concentration are available for the period 1990–2002 and the source is World Bank-World Development indicators' Database. Among the independent variables, I consider percapita GDP, from Maddison (2009) and two trends, one for democracy (*D*) and another for dictatorship (*A*), extrapolated from Przeworski's dataset (for a list of variables and sources, refer to Table 4—Data and Sources in "Appendix"). *D* (*A*) represents the number of consecutive years since the last regime change to democracy (dictatorship). It is coded 0 the year of transition to democracy (dictatorship), and 1, 2, 3 after one, two, three consecutive years of democracy (dictatorship) and so on. During periods of dictatorship (democracy) it is coded zero. The last independent variable used is *Inequality*, from the EHII dataset of the University of Texas Inequality Project (UTIP). This measure is an estimate of the Theil's index of household's income inequality derived from econometric relationships between UTP-UNIDO (dataset that calculates the industrial pay inequality measures based on the UNIDO Industrial statistics), other conditioning variables, and the World Bank's Deninger and Squire Dataset[5].

The reason for including this variable into the regression model relies mainly on the fact that it may "alter" the underlying decision process about the environmental policies undertaken in the two different regimes and—in this econometric model—its omission could bias the sign or the magnitude of the coefficients attached to democracy and/or autocracy. It is indeed well known that, from a pure theoretically point of view, in a direct democracy, a high inequality reduces the median voter's income and therefore the demand for environmental quality. In "real" representative democracies however, high levels of income inequality are often associated to a scarce participation of poorer people to the electoral process, allowing small (and often rich and strongly interested) groups of people to take all the decisions. This would make a democracy resemble from several aspects to an autocracy. During autocratic periods, however, if increased inequality is in favour of the dictator[6], it could increase environmental quality since the dictator values the environment more, compared to consumption, with respect to the population average, or simply because the opportunities to substitute environment with private consumption become scarce. So, the inclusion of this variable is done with the aim of reducing the bias that income inequality may generate in the estima-

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[5] For a detailed presentation of the techniques used to construct such an index, visit the University of Texas' website at http://utip.gov.utexas.edu/default.html.

[6] It is indeed well known that many countries in Africa and the Caribbean suffer and have suffered from "kleptocratic" regimes (Acemoglu et al. 2004) run by individulas who use their power to transfer a large fraction of society's resources to themselves. Two of the most "kleptocratic successes" are those of Mubutu Sese Seko in the Democratic Republic of Congo (Zaire) and Rafael Trujillo in the Dominican Republic. To have an idea of the numbers, in the 70's, 15–20 % of Congo's operating budget went directly to Mubutu, and in 1977 Mubutu's family took $71 million from the National Bank for personal use and in the 80's his personal fortune was estimated in $5 billion (Leslie 1987, p. 72). In the Dominican Republic, Trujillo became in power after he elected himself in a fraudulent election and at the end of his regime, the fortune of Trujillo's family amounted to about 100 % of GDP at current prices and the family "controlled almost 80 % of the country's industrial production" (Moya Pons 1995, p. 398). Other examples of "keptocratic regimes" include Haiti under the Duvaliers, Nicaragua under the Somozas, Uganda under Idi Amin, Liberia under Charles Taylor and the Philippines under Ferdinand Marcos, but the list can go on, if we include less extreme cases.

Table 1 Summary statistics of the primary explanatory variables

Variable	Description	Obs	Mean	SD	Min	Max
CO_2	Kg of carbon percapita	2,255	563.663	834.6266	0	4,470
$PM10$	Concentrations of particulate matters, micrograms per cubic meter	611	72.10575	48.19759	11.9218	274.45
GDP	Percapita GDP, 1990$	2,452	2,778.26	2,677.37	289.15	16,572.83
Dem	Dummy for Democracy (Przeworski)	2,234	.3531782	.4780645	0	1
D	Trend for Dem	2,234	3.176813	6.653377	0	44
A	Trend for (1-Dem)	2,234	10.27261	12.0507	0	50
$Ineq$	Household's income inequality (UTIP)	1,129	42.00001	6.666231	19.81	62.32
$D \cdot INEQ$	Product of inequality and the trend for democracy	1,124	160.2534	323.7205	0	1,857.66
$A \cdot INEQ$	Product of inequality and the trend for autocracy	1,124	491.798	544.5511	0	2,232.621
$Year$	Year (from 1950 to 2002)	2,491	1,976	15.30013	1,950	2,002
N		2,491				

tion of the effects the two different regimes have on the level of CO_2 emissions and PM10 concentrations.

Table 5 in "Appendix" lists all the countries included in the sample, and their respective regime changes to and from democracy. They are mainly developing countries, with the exception of the countries distinguished by an asterisk which are considered by IMF (World Economic Outlook updated to April 2009) developed or advanced. The following Table 1 shows the summary statistics of the primary explanatory variables:

4 Estimation Techniques and Results

4.1 Diagnostic Tests and Model Selection

The first step to decide the best way to estimate a relationship of interest, is to choose the appropriate econometric tool. In order to do so, it is necessary to verify the characteristics of the data generating processes, by testing for eventual unit root. I test the occurrence of unit root on the series percapita CO_2 emissions, percapita GDP, PM10 concentrations and

inequality using four tests for panel data: Levin, Lin and Chu (LLC), Im, Pesaran and Shin (IPS), ADF and PP-Fisher tests. All these tests suggest that the data generating processes of CO_2 emissions and GDP have unit root, while PM10 concentration and inequality appear stationary.[7]

For what concerns the dependent variable PM10, given its stationarity, it cannot be cointegrated with any other variable and therefore a standard least squares dummy variable (LSDV) model for testing the effects of democracy on its level is appropriate, as it should produce stationary (possibly normal) residuals.

For what concerns instead the model for CO_2 emissions, I cannot say a priori if the same LSDV model is appropriate, and a test for cointegration is mandatory so to exclude possible problems related to spurious regression.[8] If indeed the two series were cointegrated, standard OLS techniques would produce superconsistent estimates of the parameters, but if they were not, the model would suffer of the spurious regression problem with invalid inference of the parameters of interest.

In the Engle–Granger approach, cointegration is tested by verifying that the residual series generated by the regression of one I(1) variable over another I(1) variable is stationary[9]. To verify whether percapita CO_2 emissions and percapita GDP are cointegrated, I use the approach suggested by Kao (1999). The global ADF statistic for Kao residual cointegration test with the null of no cointegration shows a t stat of 3.499820 with a p value of 0.0002, so this test strongly suggests that those two series are cointegrated.

Maddala and Shaowen (1999) combined tests from individual cross-sections (trace and maximum eigenvalue tests) reject the hypothesis of absence of cointegration at 1 % level, and, as expected, accept the hypothesis that there exists one cointegrating relation.[10] So, substantial evidence points out that a cointegrating relation between emissions and income exists, so the use of a procedure that takes into account this fact is justified.

The choice of estimating the model using a single equation or a vector error correction model (VECM) is made by testing for weak exogeneity of the variables on the right-hand side of the equation describing the long run relationship of CO_2 with GDP. Estimating with a single equation when the variables are not weakly exogenous is potentially inefficient and it does not lead to the smallest variance against alternatives, because information is lost. Using the approach suggested by Urbain (1992), I test weak exogeneity by testing whether the error correction term embedded in the short run ECM[11] is significant in the equation determining ΔGDP_{it}. In particular, weak exogeneity requires that ΔGDP_{it} does not depend on disequilibrium changes represented by $\hat{\epsilon}_{it-1}$. Results of this test, deeply detailed in the "Appendix", show that GDP is weakly exogenous so the estimation of the model for CO_2 emissions using a simple equation approach is suitable for my purpose.

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[7] For a detailed description of these tests, the tests that will follow and results, refer to the "Appendix".

[8] Spurious regressions occur whenever one regresses a nonstationary variable over another nonstationary variable which are not cointegrated. In general, the estimated coefficients appear to be significant but they lack any real and plausible correlation, since what is correlated is just a common trend and nothing else. Under a spurious regression, the tendency of both series to be growing is picked up by the regression model, even though each series is growing for very different reasons and at a rates which are uncorrelated, and produce nonstationary residuals.

[9] Since in my dataset there are only two nonstationary variables, it follows that at most one cointegrating relation may exist.

[10] In performing these tests, it's been assumed that there is no deterministic trend.

[11] $\hat{\epsilon}_{it-1}$ is computed as a residual of the long run relationship explaining percapita CO_2 emissions.

4.2 Interrupted Time Series

Interrupted time series (ITS) are a powerful quasi-experimental approach for evaluating the effects of interventions. Segmented regression analysis of ITS data allows to assess, in statistical terms, how much an intervention changed an outcome of interest, immediately and over time, instantly or with delay, and whether factors other than the intervention could explain the change. In this paper, I make use of this ITS design to estimate the effects of democratisation on the level of emissions produced, in a panel of 47 countries for the period 1950–2002 for CO_2 and 1990–2002 for PM10. For each country in my sample, the levels of emissions and concentration of particulate matters, real percapita incomes and the regime are measured at regularly spaced intervals over time. To determine the effect of a regime change on the level of the two indexes of pollution, I generate two series (namely, D and A representing the number of consecutive years since the last regime change to, respectively, democracy and dictatorship) which are divided into two or more segments at changing points, when the regime type varies. So, if a country, at a given date, has shifted from dictatorship to democracy, and there is only one shift in the period taken into consideration, then the time series is divided into two segments. If the number of shifts is n, the number of segment will be, in general, $n+1$. In detail, D and A are trend variables which are evaluated progressively according to the age of the democracy or autocracy. The advantage of using those two variables is that they allow assessment of the effect of the regime through time as well whether other effects may explain the change. If indeed the coefficients relative to those trends have the same sign, this methods allows to conclude that other factors (like general technological progress) may have played a major role in the determination of the environmental policy, and not the regime.

4.3 Econometric Specifications and Results

Due to the nature of data generating process of my variables of interest, I have to specify two different models for estimating the effect of the regime on CO_2 and on the level of PM10 concentrations. Previous tests for cointegration between CO_2 and GDP suggest that those two variables have a long run relationship; they move closely together over time and their difference is stable. Test for weak exogeneity shows that GDP is weakly exogenous with respect to CO_2 so cointegration approaches which use a single equation are appropriate and no loss of information (and efficiency) occurs. For estimating the effect of the regime on the level of CO_2 emission, then, I will use the procedure proposed by Engle and Granger (1987). The Engle–Granger Error Correction Model (ECM) is appropriate in this setting and has the advantage of incorporating both long run and short run effects; if the model is in disequilibrium the ECM will provide information on the speed of adjustment to equilibrium. Moreover, all the terms in the model are stationary, and so standard regression techniques are valid, and finally, the fact that CO_2 and GDP are cointegrated of order CI(1,1) implies that an ECM exists (and, conversely, an ECM generates cointegrated series) and so ECM is immune from the spurious regression problem[12].

For what concerns the estimation of the effects of the two different regimes on the level of PM10 concentrations, I use a LSDV model to take into account of country specific fixed effects, and since tests for unit root for the PM10 series show that it is stationary, standard OLS procedures can be applied. In both econometric specifications I introduce two different trends, or, more precisely, two interrupted series of trends, D and A, which represent, respectively,

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[12] This can be referred to Granger's representation theorem for dynamic modelling, in Engle and Granger (1987)

the number of consecutive years since the last democratisation or autocratisation. During periods of dictatorship, D is coded zero, and during periods of democracy, A is coded zero. In this setup, D and A represent the effect through time on emissions or on concentration of pollution of the type of regime. The other independent variables included in the model are inequality and the cross effects of inequality with the two trends for regime. The reason for their inclusion is that depending on who is the decisive political actor in the two different regimes, inequality may have different effects.

So, on one hand, when the population as a whole is involved in the decision process (through the electoral mechanism), different levels of income inequality change the median voter's wealth and so the perceived value of income (or consumption) relative to the environmental quality, and therefore inequality is expected to worsen the environmental quality. Another reason that may induce this result is that, in reality, high income inequalities are often associated to a scarce participation of poorer people to the electoral process. This "sick participation" allows decisions to be made by a small group of people (usually rich and strongly interested) which—from a point of view—makes democracy resemble from different aspects to an autocracy.

On the other hand, during autocratic periods, if increased inequality is in favor of the dictator, it could increase environmental quality, since the rich dictator values the environment more, compared to consumption, or simply because the opportunities to substitute environment with private consumption are limited.

In order to estimate the relation between different regimes and CO_2 emissions, consider the following ARDL(1,1)

$$
CO_{2it} = \alpha_{0i} + \gamma_1 CO_{2it-1} + \sum_{j=1}^{n} \delta_{0j} X_{jit} + \sum_{j=1}^{n} \delta_{1j} X_{jit-1}
$$

$$
+ \sum_{z=3}^{4} \delta_{2z} X_{4it} X_{zit} + \sum_{z=3}^{4} \delta_{3z} X_{4it-1} X_{zit-1} + \epsilon_{it} \tag{1}
$$

with $j = 1, \ldots, 4$ and

$$
X_1 = GDP
$$
$$
X_2 = D
$$
$$
X_3 = A
$$
$$
X_4 = INEQ
$$

with some manipulations (shown in "Appendix") we end up with the usual ECM:

$$
\Delta CO_{2it} = \sum_{j=1}^{n} \delta_{0j} \Delta X_{jit} + \sum_{z=2}^{3} \delta_{2z} W_z - (1 - \gamma_1) \Big[CO_{2it-1} - \frac{\alpha_{0i}}{1 - \gamma_1}
$$

$$
- \sum_{j=1}^{n} \frac{\delta_{0j} + \delta_{1j}}{1 - \gamma_1} X_{jit-1} - \sum_{z=2}^{3} \frac{\delta_{2z} + \delta_{3z}}{1 - \gamma_1} X_{4it-1} X_{zit-1} \Big] + \eta_{it} \tag{2}
$$

$$
W_z = \Big(X_{4it} \Delta X_{zit} + \Delta X_{4it} X_{zit} - \Delta X_{4it} \Delta X_{zit} \Big) \tag{3}
$$

where the expression in square brackets represents the long run relationship between CO_2 and GDP. If the model is in equilibrium, this expression is equal to zero, and if it is not, the coefficient $-(1 - \gamma_1)$ represents the speed of adjustment toward it. Therefore, I first estimate

the long run relationship between CO_2 and the other covariates as follows:

$$CO_{2it} = \beta_{0i} + \beta_1 GDP_{it} + \beta_2 D_{it} + \beta_3 A_{it} + \beta_4 INEQ_{it}$$
$$+ \beta_5 D_{it} \cdot INEQ_{it} + \beta_6 A_{it} \cdot INEQ_{it} + \epsilon_{it} \tag{4}$$

with

$$\beta_j = \frac{\delta_{0j} + \delta_{1j}}{1 - \gamma_1} \quad j = 1, \ldots, 4$$

$$\beta_h = \frac{\delta_{2h} + \delta_{3h}}{1 - \gamma_1} \quad h = 5, 6$$

using a standar LSDV to account for specific, country-level time invariant effects (whose coefficient is represented by β_{0i}). The results of this estimation are shown in Table 2. The second step is to estimate the residuals from Eq. 4 and proceed to the estimation of the unrestricted error correction model

$$\Delta CO_{2it} = \delta_{01} \Delta GDP_{it} + \delta_{02} \Delta D_{it}^* + \delta_{03} \Delta A_{it}^* + \delta_{04} INEQ$$
$$+ \delta_{22} W_{Dit} + \delta_{23} W_{Ait} - (1 - \gamma_1)\hat{\epsilon}_{it-1} + \eta_{it} \tag{5}$$

where W_{Dit} and W_{Ait} are defined as:

$$W_{Dit} = D_{it} \cdot \Delta INEQ_{it} + \Delta D_{it}^* \cdot INEQ_{it} - \Delta D_{it}^* \cdot \Delta INEQ_{it}$$
$$W_{Ait} = A_{it} \cdot \Delta INEQ_{it} + \Delta A_{it}^* \cdot INEQ_{it} - \Delta A_{it}^* \cdot \Delta INEQ_{it}$$

and $\hat{\epsilon}_{it-1}$ is

$$\hat{\epsilon}_{it-1} = CO_{2it-1} - \beta_{0i} - \beta_1 GDP_{it-1} - \beta_2 D_{it-1} - \beta_3 A_{it-1}$$
$$- \beta_4 INEQ_{it-1} - \beta_5 D_{it-1} \cdot INEQ_{it-1} - \beta_6 A_{it-1} \cdot INEQ_{it-1}$$

Results of the estimation of Eq. 5 are shown in Table 3. Table 9 in "Appendix" shows the coefficients relative to the fixed effects estimated in Eq. 4.

As previously written, the series PM10 is stationary and therefore there cannot exist any cointegrating relation. It follows that a simple LSDV model is appropriate to estimate the effects of the regime, since the residuals are expected to be stationary (results of the tests of unit root on the residuals are shown in the "Appendix").

$$PM10_{it} = \beta_{0i} + \beta_1 GDP_{it} + \beta_2 D_{it} + \beta_3 A_{it} + \beta_4 INEQ_{it}$$
$$+ \beta_5 D_{it} \cdot INEQ_{it} + \beta_6 A_{it} \cdot INEQ_{it} + \epsilon_{it} \tag{6}$$

and the results are shown in Table 2.

As it is possible to see, the trends for democracy and dictatorship have, respectively, a negative effect on the level of emissions/pollution, in both models and all the coefficients (except that relative to inequality for the model of CO_2 emissions) are statistically significant at the standard 5 % level.

This indicates that democracy and autocracy have two different targets of "desired" pollution, with those of democracy lower than those of autocracy. Inequality per se has not a statistically significant effect on the level of CO_2 emissions or PM10 concentration, but the interaction effects between income inequality and the two regimes are highly significant, and mitigate their effects. Income inequality indeed may affect negatively the functioning of a democracy because poorer people often do not participate to the electoral process, allowing then a small, and often rich and strongly interested group of people to take all the decisions. This makes a democracy with high income inequality resemble to an autocracy. That

Table 2 Results of the estimation of the model for PM10 and the long run equilibrium relationship for CO_2

	(1) Percapita CO_2	(2) PM10
Percapita GDP	0.163***	0.00389***
	(0.00423)	(0.000867)
D	−33.32**	−4.209***
	(10.78)	(0.950)
A	37.13***	1.201***
	(2.734)	(0.350)
INEQ	−0.567	−0.264
	(1.900)	(0.148)
D · INEQ	0.762**	0.0475*
	(0.243)	(0.0204)
A · INEQ	−0.786***	−0.0259**
	(0.0664)	(0.00780)
N	1,100	310

t Statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

is the reason why democracy interacted with inequality is positive (while democracy alone is negative on the level of emissions/concentrations). The same reasoning can be applied to the interaction effect between autocracy and inequality. Given the fact that in autocracy the level of environmental quality is lower than in a democracy, it might be that if inequality goes in favour of the dictator (see footnote 6 for some examples) he could start to value the environment more, compared to private consumption, or it might be also that the possibility to substitute environment with private consumption starts to be scarce. So, given the fact that in autocracy the level of pollution is higher, inequality (in favour of the dictator) might mitigate this effect because of those two reasons.

For model 1 (PM10), the elasticity of concentration of PM10 with respect to one year increase in democracy ($\partial PM10/\partial D$), computed at the mean of inequality is equal to −2.14, and the same elasticity computed for one year increase in dictatorship ($\partial PM10/\partial A$) is 0.1132. For the second model, relative to CO_2 emissions, $\partial CO_2/\partial D = -1.316$ and $\partial CO_2/\partial A = 1.118$. It is possible to say therefore that in both models (even in the second all the conclusions apply only to the long run period) democracy is good for the environment, and moreover the argument is reinforced by the fact that non-democracies are not. Table 3 shows the results from the estimation of the unrestricted ECM for CO_2 emissions:

The main results are reported in Table 3. Variations in the level of CO_2 are, of course, positively related to variations in global production, and the coefficient attached to $\hat{\epsilon}$ represents the speed of adjustment towards the equilibrium. It is worth noting that the coefficient related to ΔD^*_{it} is not significant at the standard 5% level (in fact, it has a p value of 0.574), while the coefficient related to the variation in the trend for dictatorship is positive and significatively related to increases in the variation of emissions. This effect may be the cause of the slower reactions of democracies with respect to autocracies. Democracies are indeed constrained by consultations, elections, every decisions has often to pass the evaluations of another independent organism, and this procedure takes time. On the contrary, in dictatorship the decisions are taken by one individual only and they have not to be scrutinised by other

Table 3 Unrestricted error correction model for CO_2 emissions		Δ Percapita CO_2
	Δ Percapita GDP_{it}	0.0938***
		(0.0104)
	$\hat{\epsilon}_{it-1}$	−0.128***
		(0.0160)
	ΔD_{it}^*	−11.50
		(14.45)
	ΔA_{it}^*	34.13**
		(12.19)
	$\Delta INEQ_{it}$	−2.629*
		(−1.298)
	W_{Dit}	0.579***
		(0.168)
t Statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	W_{Ait}	0.00380
		(0.0549)
	N	1,033

independent powers. The reasons for this non-significancy for the variations of the democratic level on the variation of emissions is probably to to this difference in the time a policy takes to be implemented into the two different regimes.

5 Conclusion

Despite the different views about the effect of democracy on the environmental management, in this paper I show that democracy and environmental quality are positively correlated. To show that, I use the powerful approach of ITS design in cointegration analysis to show that democratic countries and autocratic ones have two different targets of environmental quality, with those for democracy higher than those for autocracies. Previous works on democracy and environmental quality were indeed unable to assert that democracy is really good for the environment because they did not show that non-democracies are not. Segmented regression analysis of ITS allows not only to see the effect of democracy through time, but also if this effect differs from the effect of autocracy. The weakness of the previous works in this field was therefore that not comparing the results with those for dictatorships, the positive effect of democracy on the environment might not be due to democracy per se, but from other effects, like maturation, or technological progress, common to both regimes. In this panel of 47 transition countries, this approach shows that democratisation is consistently associated to a reduction of CO_2 emissions and PM10 concentrations, but this process may be quite slow because—at least in the ECM relative to CO_2 emissions—it is detectable only in the long run. Due to the fact that democratic institutions tend to be slower than autocratic ones in taking decisions and acting, in the short run we do not observe a negative effect of democracy on the level of emissions, while the positive effect of dictatorship is quite consistent. Inequality has two different effects depending on the incumbent regime: in any case it counterbalances the global effect of the regime. In democracy, increased inequality means that the decisive citizen is poorer and so less willing to pay for environmental protection. This however assuming perfect democracy only and full participation to the poll. From another point of view, it is

reasonable to think that democratic institutions work worse when inequality is high, due to the scarce participation of the poor to the electoral processes, and therefore democracies with high income inequality resemble more to a dictatorship than a democracy itself, because decisions are taken by a small (and usually strongly interested) group of people. Inequality during periods of autocracy, under the assumption that this inequality favors the dictator at the expense of the rest of the citizens, it may retain the negative effect of the regime since it increases the dictator's income and so it increases his demand for environmental quality, which may be driven by a limited (although high) opportunity to substitute environment with private consumption. The overall effect, however, is that dictatorships tend to be associated to a worse environment than democracies.

Appendix

Diagnostic Tests

Panel Unit Root Test

The first step to decide the best way to estimate a relationship of interest, is to choose the appropriate econometric tool. In order to do so, it is necessary to verify the characteristics of the data generating processes: for each nondeterministic series (CO_2 emissions, percapita GDP, PM10 concentrations and Inequality), I test whether they have stationary mean and variance. Available tests for unit root on panel data are based on the Dickey Fuller test (or its augmented version), so I test the following:

$$y_{it} = \rho_i y_{it-1} + X'_{it}\delta_i + \epsilon_{it} \tag{7}$$

with $i = 1, \ldots, N$ and $t = 1, \ldots, T_i$. ρ_i represents the autoregressive coefficient for country i, X_{it} is matrix representing the exogenous variables in the model, including any fixed effects and individual trends and ϵ_{it} are the errors which are assumed i.i.d. If $|\rho_i| = 1$, then y_i contains a unit root. For practical purpose, the tests for unit root are performed using the following basic ADF specification:

$$\Delta y_{it} = \alpha_i y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X'_{it}\delta_i + \epsilon_{it} \tag{8}$$

with $\alpha_i = \rho_i - 1$.

Levin, Lin and Chu test assumes that the unit root process is common to all the cross sections so it assumes $\alpha_i = \alpha$ for every i. The test is performed by testing the null hypothesis $H_0 : \alpha = 0$ against the alternative $H_1 : \alpha < 0$ for all the cross section units. Their procedure derives estimates of α from proxies for Δy_{it} and y_{it} that are standardised and free of autocorrelation and deterministic components. For a given set of lag orders p_i, their procedure begins by estimating two additional sets of equations,

$$\Delta y_{it} = \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X'_{it}\delta \tag{9}$$

$$y_{it} = \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X'_{it}\delta \tag{10}$$

and denoting $(\hat{\beta}, \hat{\delta})$ the estimated coefficients of Eq. 9 and $(\dot{\beta}, \dot{\delta})$ those of Eq. 10. They define, then, $\Delta \bar{y}_{it}$ and $\bar{y}_{it-1}$ by taking, respectively, Δy_{it} and y_{it-1} and removing the autocorrelations and deterministic components using their respective auxiliary estimates

$$\Delta \bar{y}_{it} = \Delta y_{it} - \sum_{j=1}^{p_i} \hat{\beta}_{ij} \Delta y_{it-j} - X'_{it} \hat{\delta} \tag{11}$$

$$\bar{y}_{it-1} = y_{it-1} - \sum_{j=1}^{p_i} \dot{\beta}_{ij} \Delta y_{it-j} - X'_{it} \dot{\delta} \tag{12}$$

and standardise both $\Delta \bar{y}_{it}$ and $\bar{y}_{it-1}$ by dividing by the regression standard error

$$\Delta \tilde{y}_{it} = \frac{\Delta \bar{y}_{it}}{s_i}$$

$$\tilde{y}_{it-1} = \frac{\bar{y}_{it-1}}{s_i}$$

where s_i are the estimated standard errors from estimating each ADF in Eq. 8. The estimate of α is then obtained from the pooled proxy equation

$$\Delta \tilde{y}_{it} = \alpha \tilde{y}_{it-1} + \eta_{it} \tag{13}$$

which, under the null, a modified t statistics for the resulting $\hat{\alpha}$ is asymptotically normally distributed

$$t^*_\alpha = \frac{t_\alpha - (\tilde{N}T) S_N \hat{\sigma}^{-2} se(\hat{\alpha}) \mu_{m\tilde{T}*}}{\sigma_{m\tilde{T}*}} \to N(0, 1)$$

where t_α is the standard statistic for $\hat{\alpha} = 0$, $\hat{\sigma}^2$ is the estimated variance of the error term η, $se(\hat{\alpha})$ is the standard error of $\hat{\alpha}$, and

$$\tilde{T} = T - \left(\sum_i p_i / N \right) - 1,$$

S_N is the mean of the ratios of the long run standard deviation for each individual, and it is estimated using kernel-based techniques, and $\mu_{m\tilde{T}*}$ and $\sigma_{m\tilde{T}*}$ are adjustment terms for the mean and standard deviation (for more details, refer to the original article of Levin et al. 2002). In order to perform this test, I include individual constant terms (fixed effects), and an individual trend, so my X_{it} matrix is a $2NT \times 2N$ matrix, where the first $NT \times N$ block is a matrix of dummy variables, each representing one single country, and the other block going from row $NT + 1$ to $2NT$ and from column $N + 1$ to $2N$ is a matrix of trends, one for each single countries. All the other terms in the matrix are equal to zero.

If the test for common unit root fails, it might be convenient to check whether individual unit root exists. Tests available for that are Im, Peasaran and Shin, Fisher AD and PP tests. Im, Pesaran and Shin test begin by specifying a separate ADF regression for each cross-section according to Eq. 8 with the null

$$H_0 : \alpha_i = 0 \text{ for every } i = 1, 2, \ldots, N$$

and the alternative hypothesis is

$$H_1 : \begin{cases} \alpha_i = 0 & \text{for } i = 1, 2, \ldots, N_1 \\ \alpha_i < 0 & \text{for } i = N_1 + 1, N_1 + 2, \ldots, N \end{cases}$$

That can be interpreted as a nonzero fraction of the individual processes is stationary. After having estimated the separate ADF regressions, the average of the t statistics for α_i from the individual ADF regressions, $t_{iT_i}(p_i)$,

$$\bar{t}_{NT} = \left(\sum_{i=1}^{N} t_{iT_i}(p_i)\right)/N$$

is adjusted to arrive to the desired statistics. Critical values are provided in the Im, Pesaran and Shin's paper (2003) for different number of cross sections and time periods when $p_i = 0$ for all i, but in the general case when the lag order in Eq. 8 may be nonzero for some cross-sections, they show that a properly standardised $\bar{t}_{NT}$ has an asymptotic standard normal distribution

$$W_{\bar{t}_{NT}} - \frac{\sqrt{N}\left(\bar{t}_{NT} - N^{-1}\sum_{i=1}^{N} E(\bar{t}_{iT}(p_i))\right)}{\sqrt{N^{-1}\sum_{i=1}^{N} Var(\bar{t}_{iT}(p_i))}} \rightarrow N(0, 1)$$

and the expression for the expected mean and variance of the ADF regression t statistics, $E(\bar{t}_{iT}(p_i))$ and $Var(\bar{t}_{iT}(p_i))$ are provided by Im, Pesaran and Shin for various values of T and p and different test equation assumptions. I will use, in this paper, one lag and, as deterministic component, an individual constant, without introducing any trend term. Finally, there are other two tests for checking individual unit root: Fisher ADF and Fisher PP tests, which are based upon the idea by Maddala, Wu and Choi, and combine the p values from individual unit root tests. They work as follows: define π_i the p value from individual unit root test for cross-section i, then under the null of unit root for all the N cross sections, we have the asymptotic result that

$$-2\sum_{i=1}^{N} \log(\pi_i) \rightarrow \chi^2_{2N}$$

and also, Choi demonstrates that

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}(\pi_i) \rightarrow N(0, 1)$$

where Φ^{-1} is the inverse of a standard normal cumulative distribution function. For both the Fisher tests, I specify as exogenous variables an individual constant (fixed effect) and an individual time trend.

Table 6 in "Appendix" shows the results of the tests for all the nondeterministic series. These tests accept the hypothesis of unit root only for two out of four series, percapita GDP and percapita CO_2 emissions. Since the level of concentration of particulate matters (PM10) is stationary, it cannot be cointegrated with any other variable, while in principle CO_2 and GDP could be. For what concerns the dependent variable PM10, then, a standard Least Squares Dummy Variables (LSDV) model for testing the effect of democracy on its level it is appropriate, as it should produce stationary (possibly normal) residuals. For what concerns the model for CO_2 emissions, we cannot say a priori whether the same LSDV model is appropriate, and a test for cointegration is mandatory. If indeed the two series were cointegrated, that model would produce superconsistent estimates of the parameters, but if they were not, the model would suffer of the problem of the spurious regression with invalid inference of the parameters of interest. In this case, the tendency of both series to be growing

leads to correlation which is picked up by the regression model, even though each series is growing for very different reasons and at a rates which are uncorrelated. Thus, in absence of cointegration (which will be tested in the next subsection) correlation between non-stationary series does not imply the kind of causal relationship that might be inferred from stationary series, so standard estimation techniques like OLS cannot be used.

Panel Cointegration Test

If two or more variables are nonstationary or I(1), if they are not cointegrated, the residual series obtained by regressing one I(1) variable over another I(1) variable is expected to be nonstationary, or I(1). This would lead to spurious regression since the estimated coefficients do not reflect a real relationship between those two variables, but simply correlated time trends. This however would be different if those two variables were cointegrated, and the coefficients would benefit from the "superconsistency" property. Since in my dataset there are only two nonstationary variables, namely, CO_2 and GDP, it follows that at most one cointegrating relation may exist. In the Engle–Granger approach, cointegration is tested by verifying that the residual series generated by the regression of one I(1) variable over another I(1) variable is stationary. To verify whether percapita CO_2 emissions and percapita GDP are cointegrated, I use the approach suggested by Kao (1999). Kao uses a two-step procedure to test for cointegration: in the first step, he regress the dependent variable [which is I(1)] over the independent [also I(1)] specifying cross-section specific intercepts and homogeneous coefficient: he basically regresses

$$CO_{2it} = X'_{it}\alpha_i + \beta GDP_{it} + e_{it} \tag{14}$$

where X_{it} is a matrix of dummy variables representing each single country and assuming $CO_{2it} = CO_{2it-1} + u_{it}$ and $GDP_{it} = GDP_{it-1} + \epsilon_{it}$ for $t = 1, \ldots, T$ and $i = 1, \ldots, N$. Then Kao runs the pooled auxiliary regression

$$e_{it} = \rho e_{it-1} + \sum_{j=1}^{p} \psi_j \Delta e_{it-j} + v_{it} \tag{15}$$

Assuming $p = 1$[13], this augmented Dikey Fuller test for panel data reject at 1 % level the hypothesis that $\rho = 1$. The global ADF t statistic for Kao residual cointegration test with the null hypothesis of no cointegration shows a t stat of 3.499820 with a p value of 0.0002, so this test strongly suggests that those two series are cointegrated (detailed results of this test are in this Table 7 in "Appendix").

Maddala and Shaowen (1999) combined test from individual cross-sections[14] is specified as follows: consider the following VAR representation for each cross-section unit:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \epsilon_t \tag{16}$$

where Y is a vector of I(1) variables (in my case, CO_2 and GDP). Subtracting Y_{t-1} on the left and right hand side of equation 16 and adding and subtracting $A_2 Y_{t-1}$ from the right hand side, we get

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma \Delta Y_{t-1} + \epsilon_t \tag{17}$$

with $\Pi = (A_1 + A_2 - I)$ and $\Gamma = -A_2$. Granger's representation theorem asserts that if the coefficient matrix Π has a reduced rank $r < k$, then there exists kxr matrices α and β

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[13] Similar results are obtained for longer lags specifications, up to four.

[14] Maddala and Wu use the results obtained by Fisher (1932).

each with rank r such that $\Pi = \alpha \cdot \beta'$ and $\beta' Y_t$ is I(0). r is the number of cointegrating relations and each column of β is the cointegrating vector, and the elements of α are known as the adjustment parameters in the VEC model. Johansen's method is to estimate the Π matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π. In performing this test, I assume that the level data Y_t have no deterministic trends and the cointegrating equations have only intercepts, so

$$H(r): \Pi Y_{t-1} = \alpha(\beta' Y_{t-1} + \rho_0) \tag{18}$$

To determine the number of cointegrating relations r conditional on assumption 18, we proceed sequentially from $r = 0$ to $r = k - 1$ until we fail to reject. The trace statistic for the null hypothesis of r cointegrating relations is computed as

$$LR_{tr}(r|k) = -T \sum_{i=r+1}^{k} log(1 - \lambda_i) \tag{19}$$

where λ_i is the largest eigenvalue of the Π matrix.

The maximum eigenvalue statistic tests the null hypothesis of r cointegrating relations against the alternative of $r + 1$ relations. The test statistics is computed

$$LR_{max}(r|r+1) = -T \cdot log(1 - \lambda_{r+1})$$
$$= LR_{tr}(r|k) - LR_{tr}(r+1|k) \tag{20}$$

If the test statistics are continuous, the significance levels for each cross-section unit, denoted by π_i for $i = 1, 2, \ldots, N$, are independent uniform (0,1) variables, and $-2 \log \pi_i$ has a χ^2 distribution with two degrees of freedom. The approach proposed by Maddala and Wu to test cointegration in panel is to combine tests from individual cross sections to obtain a test statistic for the full panel, using the additive property of the χ^2 variables: if π is the p value from an individual cointegration test for the cross-section i, under the null hypothesis for the panel we have

$$-2 \sum_{i=1}^{N} log(\pi_i) \rightarrow \chi^2_{2N} \tag{21}$$

Both trace and maximum eigenvalue tests reject the hypothesis of absence of cointegration at 1 % level, and accept the hypothesis that there exists one cointegrating relation[15]. So, substantial evidence points out that a cointegrating relation between emissions and income exists, so the use of a procedure that takes into account this fact is justified.

Weak Exogeneity Test

In the model for the estimation of the of the effect of the regime on the level of CO_2 emissions, I have only two non-stationary series, while the other variables are either deterministic or I(0). It follows that only one cointegrating relation can exist, so in principle it is possible to estimate this relationship using a single equation. However, estimating with a single equation is not free of drawbacks, as it is potentially inefficient, and so it does not lead to the smallest variance against alternative approaches. In general, information is lost unless the right-hand side variables in the cointegration vector are weakly exogenous. Weak exogeneity of these variables is indeed a prerequisite to assert that no useful information is lost when we condition

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[15] In performing this test, it's been assumed that there is no deterministic trend.

on these variables without specifying their generating process. In practical terms, it must be the case that GDP is weakly exogenous with respect to the level of CO_2 emissions. As pointed out by Urbain (1992), testing for weak exogeneity requires testing whether the error-correction term embedded in the short-run ECM ($\hat{\epsilon}_{it-1}$ computed as a residual of the long run relationship equation) is significant in the equation determining ΔGDP_{it}. In particular, weak exogeneity requires that ΔGDP_{it} does not depend on the disequilibrium changes represented by $\hat{\epsilon}_{it-1}$.

Consider the following long run relationship for the dependent variable percapita CO_2 emissions:

$$CO_{2it} = \beta_{0i} + \beta_1 GDP_{it} + \beta_2 D_{it} + \beta_3 A_{it} + \beta_4 INEQ_{it}$$
$$+ \beta_6 D_{it} \cdot INEQ_{it} + \beta_7 A_{it} \cdot INEQ_{it} + \epsilon_{it} \tag{22}$$

where the betas are combinations of parameters deriving from the ARDL model (for more details, please refer to the "Appendix"). Testing for weak exogeneity requires, in order:

1. Estimating the coefficients of Eq. 22
2. Computing the estimated residual series as

$$\hat{\epsilon}_{it} = CO_{2it} - \hat{\beta}_{0i} - \hat{\beta}_1 GDP_{it} - \hat{\beta}_2 D_{it} - \hat{\beta}_3 A_{it} - \hat{\beta}_4 INEQ_{it} +$$
$$- \hat{\beta}_6 D_{it} \cdot INEQ_{it} - \hat{\beta}_7 A_{it} \cdot INEQ_{it}$$

3. Estimating the following equation[16]:

$$\Delta GDP_{it} = \gamma_1 \Delta CO_{2it} + \gamma_2 \Delta D_{it}^* + \gamma_3 \Delta A_{it}^* + \gamma_4 \Delta INEQ_{it}$$
$$+ \gamma_5 W_{Dit} + \gamma_6 W_{Ait} - (1-\alpha)\hat{\eta}_{it-1} + \delta\hat{\epsilon}_{it-1} \tag{23}$$

where the short-run interaction effects between the two trends and inequality are

$$W_{Dit} = D_{it} \cdot \Delta INEQ_{it} + \Delta D_{it}^* \cdot INEQ_{it} - \Delta D_{it}^* \cdot \Delta INEQ_{it}$$
$$W_{Ait} = A_{it} \cdot \Delta INEQ_{it} + \Delta A_{it}^* \cdot INEQ_{it} - \Delta A_{it}^* \cdot \Delta INEQ_{it}$$

and $\hat{\eta}_{it}$ is the error correction term for the equation defining the relationship between GDP and CO_2, and it is estimated from the long run relationship between GDP and CO_2, given by

$$GDP_{it} = \theta_{0i} + \theta_1 CO_2 + \theta_2 D_{it} + \theta_3 A_{it} + \theta_4 INEQ_{it}$$
$$+ \theta_6 D_{it} \cdot INEQ_{it} + \theta_7 A_{it} \cdot INEQ_{it} + \eta_{it} \tag{24}$$

and $\hat{\epsilon}_{it-1}$ is already defined at point 2.

4. Checking and testing the significancy of the coefficient attached to $\hat{\epsilon}_{it-1}$, δ, in the equation defined at point 3. If δ is significant in Eq. 23, then we cannot say that GDP is weakly exogenous and then a multivariate model for estimation is necessary. If instead δ is found to be non-significant, a standard error correction model with one single equation is enough to estimate efficiently the relations of interest, so no loss of information occurs.

Results from the estimation of Eq. 23 for CO_2 show that t test for δ accepts the null of $\delta = 0$ at the standard level of 5 %. This coefficient amounts to -0.0382668, with a standard error of 0.1013909, a t statistic of -0.38 and a p value of 0.706, so GDP is shown to be weakly exogenous.

It is possible to conclude, then, that the estimation of the model for CO_2 emissions using a single equation approach is appropriate, and there is no loss of information (and efficiency) (Tables 4, 5, 6, 7, 8, 9, 10).

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[16] ΔD^* and ΔA^* are equal, respectively, to $\Delta D \cdot Dem$ and $\Delta A \cdot (1 - Dem)$.

Table 4 Data and sources

Variable	Description	Source
Democracy variable, Dem	Data for the period 1951–2002, it is coded 1 when the regime can be classified as democratic, 0 otherwise. It is equal to 1-REG , where REG is the the index in Przeworski's database "REG02" that is coded 1 if a country is under dictatorship, 0 otherwise	Adam Przeworski, http://politics.as.nyu.edu/object/przeworskilinks.html
CO_2	Percapita emissions of CO_2 estimates expressed in metric tons of carbon	Marland et al. (2008). *Global, Regional, and National CO_2 Emissions*. In "Trends: A Compendium of Data on Global Change". Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., http://cdiac.ornl.gov/trends/emis/overview.html
Year	Year the observation is referred to. 1951–2006	–
GDP	Percapita GDP in in 1990 GK\$. GK refers to the method used to estimate this data (Geary–Khamis method). For a description of the methodology, see reference United Nations (1992)	Angus Maddison, http://www.ggdc.net/maddison/
Democracy Trend, D	This variable indicates how many subsequent years a country has been democratic. It is coded 0 the year of the switch to democracy, and 1, 2, 3 etc., after one, two or three periods since democratisation, if further switches have not took place. It is coded 0 if Democracy variable is equal to 0	Data elaborated from Przeworski's datasets, http://politics.as.nyu.edu/object/przeworskilinks.html
Dictatorship Trend, A	This variable indicates how many subsequent years a country has been autocratic. It is coded 0 the year of the switch to dictatorship, and 1, 2, 3 etc., after one, two or three periods since autocratisation, if further switches have not took place. It is coded 0 if Democracy variable is equal to 1	Data elaborated from Przeworski's datasets, http://politics.as.nyu.edu/object/przeworskilinks.html
Inequality	Theil index of household's income inequality (EHII dataset), annual observations	University of Texas Income Inequality Project (UTIP) http://utip.gov.utexas.edu/data.html
PM10	Annual average concentration level of particulate matters expressed in micrograms per cubic meter	World Bank, World Development indicators (WDI) http://databank.worldbank.org/ddp/home.do?Step=1\&id=4

Table 5 Regime changes (year)

Country	No.	Przeworski (1950–2002) Switch to dem.	Switch to dict.
Albania	1	1992	–
Bangladesh	1	1991	–
Bolivia	3	1979, 1982	1980
Brazil	2	1979	1964
Bulgaria	1	1990	–
Burundi	2	1993	1996
Central Afr. Rep.	1	1993	–
Chile	2	1990	1973
Colombia	1	1958	–
Congo (Brazzaville)	2	1992	1997
Cote d'Ivoire	1	2000	–
Czechoslovakia*	1	1990	–
Ecuador	3	1979	1963, 2000
El Salvador	1	1984	–
Ghana	5	1969, 1979, 1993	1972, 1981
Greece*	2	1974	1967
Guinea-Bissau	1	2000	–
Haiti	1	1994	–
Hungary	1	1990	–
Indonesia	1	1999	–
Kenya	1	1998	–
Korea Rep.*	3	1960, 1988	1961
Laos	1	-	1959
Lesotho	1	1993	–
Madagascar	1	1993	–
Malawi	1	1994	–
Mali	1	1992	–
Mexico	1	2000	–
Moldova	1	1996	-
Nepal	2	1991	2002
Nicaragua	1	1984	–
Niger	3	1993, 2000	1996
Nigeria	4	1979, 1999	1966, 1983
Pakistan	5	1972, 1988	1956, 1977, 1999
Panama	3	1852, 1989	1968
Peru	7	1956, 1963, 1980, 2001	1962, 1968, 1990
Philippines	2	1986	1965
Poland	1	1989	–
Portugal*	1	1976	–
Romania	1	1990	–
Senegal	1	2000	–

Table 5 continued

Country	Przeworski (1950–2002)		
	No.	Switch to dem.	Switch to dict.
Sierra Leone	4	1996, 1998	1967, 1997
South Africa	1	1994	–
Spain*	1	1977	–
Sri Lanka	2	1989	1977
Venezuela	1	1959	–
Zambia	1	1991	–

Table 6 Panel unit root test summary

Exogenous variables: individual effect and individual trend lags included: 1

Method	Stat.	Prob**	Cross section	Obs
Series: CO_2				
Null: common unit root process				
Levin, Lin & Chu	1.58923	0.9440	46	2, 164
Null: individual unit root process				
Im, Pesaran and Shin W-Stat	3.77347	0.9999	46	2, 164
ADF-Fisher Chi square	55.8579	0.9989	46	2, 164
PP-Fisher Chi square	106.053	0.1501	46	2, 210
Series : PM10				
Null: common unit root process				
Levin, Lin & Chu	−19.4936	0.0000	47	517
Null: individual unit root process				
Im, Pesaran and Shin W-Stat	−3.13628	0.0009	47	517
ADF-Fisher Chi square	131.894	0.0061	47	517
PP-Fisher Chi square	188.949	0.0000	47	564
Series : GDP				
Null: common unit root process				
Levin, Lin & Chu	−0.20043	0.4206	47	2357
Null: individual unit root process				
Im, Pesaran and Shin W-Stat	3.46602	0.9997	47	2,357
ADF-Fisher Chi square	66.3949	0.9862	47	2,357
PP-Fisher Chi square	58.8221	0.9983	47	2,404
Series : Inequality				
Null: common unit root process				
Levin, Lin & Chu	−5.08281	0.0000	37	973
Null: individual unit root process				
Im, Pesaran and Shin W-Stat	−3.28362	0.0005	37	973
ADF-Fisher Chi square	139.410	0.0000	37	973
PP-Fisher Chi square	231.032	0.0000	37	1,026

All other tests assume asymptotic normality

** Probabilities for Fisher tests are computed using an asymptotic Chi square distribution

Table 7 Kao residual cointegration test for CO_2 and GDP

Included observations: 2,491
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend

	t stat	Prob
ADF	3.499820	0.0002
Residual variance	32,630.21	
HAC variance	54,563.01	

Augmented Dickey Fuller test equation
Dependent variable: $\Delta\hat{\epsilon}_{it}$
Method: least squares
Included observations: 2,164

Variable	Coeff.	SE	t stat	Prob
$\hat{\epsilon}_{it-1}$	-0.010256	0.005722	-1.792398	0.0732
$\Delta\hat{\epsilon}_{it-1}$	0.026135	0.021942	1.191083	0.2338

Table 8 Johansen Fisher panel cointegration test for CO_2 and GDP

Included observations: 2,491
Trend assumption: No deterministic trend (restricted constant)
Lags interval (in first difference): 1 1
Unrestricted cointegration rank test (trace and maximum eigenvalue)

Hypothesized no. of CE(s)	Fisher stat* from trace test	Prob	Fisher stat* from max eigen. test	Prob
None	185.7	0.0000	180.7	0.0000
At most 1	83.10	0.7353	83.10	0.7353

*Prob are computed using asymptotic Chi square distribution

The Econometric Model for the Estimation of the Unrestricted ECM for CO_2 Emissions

Consider the following ARDL(1,1)

$$CO_{2it} = \alpha_{0i} + \gamma_1 CO_{2it-1} + \sum_{j=1}^{n} \delta_{0j} X_{jit} + \sum_{j=1}^{n} \delta_{1j} X_{jit-1}$$

$$+ \sum_{z=3}^{4} \delta_{2z} X_{4it} X_{zit} + \sum_{z=3}^{4} \delta_{3z} X_{4it-1} X_{zit-1} + \epsilon_{it} \qquad (25)$$

with $j = 1, \ldots, 4$ and

$$\begin{aligned} X_1 &= GDP \\ X_2 &= \sqrt{D} \\ X_3 &= \sqrt{A} \\ X_4 &= Ineq \end{aligned} \qquad (26)$$

Table 9 Fixed effects coefficients of the long run equilibrium relationship of CO_2 and of the model for PM10 concentrations

	PM10	Percapita CO_2		PM10	Percapita CO_2
Albania	10.82	259.18**	Madagascar	0	267.21**
	(8.66)	(89.34)		(·)	(78.93)
Bangladesh	171.62***	355.07***	Malawi	31.39**	404.56***
	(9.65)	(78.63)		(9.49)	(77.31)
Bolivia	91.57***	293.52***	Mali	0	0
	(8.70)	(74.90)		(·)	(·)
Brazil	10.72	0	Mexico	−8.10	333.00***
	(7.31)	(·)		(6.62)	(76.84)
Bulgaria	45.24***	1,397.27***	Moldova	18.13*	583.79***
	(6.58)	(75.63)		(8.04)	(87.08)
Burundi	17.77	377.42***	Nepal	24.30*	351.98***
	(10.52)	(81.69)		(9.41)	(87.10)
Central African Rep.	23.62*	338.22***	Nicaragua	0	93.36**
	(9.88)	(80.69)		(·)	(78.40)
Chile	16.40**	155.91*	Niger	0	0
	(5.62)	(73.70)		(·)	(·)
Colombia	53.95***	196.93**	Nigeria	104.95***	444.79***
	(9.89)	(75.38)		(9.20)	(77.09)
Congo	0	296.97	Pakistan	180.17***	359.77***
	(·)	(83.18)		(9.49)	(78.69)
Cote d'Ivoire	33.08**	303.43***	Panama	16.39*	132.49
	(9.58)	(78.72)		(6.73)	(73.90)
Czechoslovakia	23.44***	2,644.76***	Peru	42.03***	172.74*
	(6.27)	(79.98)		(8.04)	(81.01)
Ecuador	11.64	229.94 **	Philippines	28.76**	302.77***
	(7.74)	(79.69)		(8.62)	(75.07)
El Salvador	25.65**	163.84*	Poland	2.28	2,133.87***
	(8.74)	(76.03)		(6.31)	(77.00)
Ghana	2.03	335.64***	Portugal	0	−35.81
	(9.84)	(78.07)		(·)	(75.57)
Greece	27.70***	532.61***	Romania	−8.69	1,235.64***
	(4.65)	(74.78)		(7.91)	(78.46)
Guinea-Bissau	0	0	Senegal	54.47***	308.57***
	(·)	(·)		(8.97)	(77.42)
Haiti	0	272.89**	Sierra Leone	54.87***	457.79**
	(·)	(80.15)		(12.02)	(131.19)
Hungary	−19.75**	1,059.52***	South Africa	−17.63*	2,066.30***
	(6.20)	(76.01)		(7.38)	(75.04)
Indonesia	72.13***	231.20**	Spain	−3.68	252.07**
	(7.84)	(76.86)		(4.21)	(76.18)

Table 9 continued

	PM10	Percapita CO2		PM10	Percapita CO2
Kenya	15.53	373.75***	Sri Lanka	57.10***	125.22
	(9.04)	(76.17)		(7.93)	(77.25)
Korea Rep.	−12.45**	596.39***	Venezuela	16.38*	512.39***
	(5.10)	(74.52)		(7.21)	(75.09)
Laos	0	0	Zambia	59.13***	520.78***
	(·)	(·)		(10.51)	(80.79)
Lesotho	40.91***	0	c	48.57***	−437.49***
	(9.74)	(·)		(11.19)	(107.19)

Standard errors in parentheses
$* p < 0.05, ** p < 0.01, *** p < 0.001$

Table 10 Panel unit root test summary

Exogenous variables: none
Lags included: 1

Method	Stat.	Prob**	Cross section	Obs
Series : Residuals from the estimation of the long run relationship of CO2 and the other covariates (ref. Table 2)				
Null: vommon unit root process				
Levin, Lin & Chu	-7.72560	0.0000	40	971
Null: individual unit root process				
ADF-Fisher Chi square	211.779	0.0000	40	971
PP-Fisher Chi square	303.568	0.0000	46	1030
Series : Residuals from the estimation of the relationship of PM10 and the other covariates (ref. Table 2)				
Null: common unit root process				
Levin, Lin & Chu	-7.96817	0.0000	25	206
Null: individual unit root process				
ADF-Fisher Chi square	123.941	0.0000	25	206
PP-Fisher Chi square	157.196	0.0000	25	206

All other tests assume asymptotic normality
**Probabilities for Fisher tests are computed using an asymptotic Chi square distribution

with some manipulations

$$
\mathrm{CO2}_{it} - \mathrm{CO2}_{it-1} + \mathrm{CO2}_{it-1} = \alpha_{0i} + \gamma_1 CO2_{it-1} + \sum_{j=1}^{n} \delta_{0j} X_{jit} + \sum_{j=1}^{n} \delta_{1j} X_{jit-1}
$$

$$
+ \sum_{j=1}^{n} \delta_{0j} X_{jit-1} - \sum_{j=1}^{n} \delta_{0j} X_{jit-1} + \sum_{z=2}^{3} \delta_{2z} X_{4it} X_{zit}
$$

$$
+ \sum_{z=2}^{3} \delta_{3z} X_{4it-1} X_{zit-1} + \epsilon_{it}
$$

$$\Delta \text{CO}_{2it} = \alpha_{0i} - (1 - \gamma_1)CO2_{it-1} + \sum_{j=1}^{n} \delta_{0j} \Delta X_{jit}$$

$$+ \sum_{j=1}^{n} (\delta_{0j} + \delta_{1j}) X_{jit-1}$$

$$+ \sum_{z=2}^{3} \delta_{2z} X_{4it} X_{zit} + \sum_{z=2}^{3} \delta_{3z} X_{4it-1} X_{zit-1} + \epsilon_{it}$$

$$= \alpha_{0i} - (1 - \gamma_1)\text{CO}_{2it-1} + \sum_{j=1}^{n} \delta_{0j} \Delta X_{jit}$$

$$+ \sum_{j=1}^{n} (\delta_{0j} + \delta_{1j}) X_{jit-1}$$

$$- \sum_{z=2}^{3} \delta_{2z} \Delta X_{4it} \Delta X_{zit} + \sum_{z=3}^{4} (\delta_{2z} + \delta_{3z}) X_{4it-1} X_{zit-1}$$

$$+ \sum_{z=2}^{3} \delta_{2z} X_{4it} \Delta X_{zit} + \sum_{z=2}^{3} \delta_{2z} \Delta X_{4it} X_{zit}$$

and we end up with the usual ECM:

$$\Delta \text{CO}_{2it} = \sum_{j=1}^{n} \delta_{0j} \Delta X_{jit} + \sum_{z=2}^{3} \delta_{2z} W_z - (1 - \gamma_1) \Big[\text{CO}_{2it-1} - \frac{\alpha_{0i}}{1 - \gamma_1}$$

$$- \sum_{j=1}^{n} \frac{\delta_{0j} + \delta_{1j}}{1 - \gamma_1} X_{jit-1} - \sum_{z=2}^{3} \frac{\delta_{2z} + \delta_{3z}}{1 - \gamma_1} X_{4it-1} X_{zit-1} \Big]$$

$$W_z = \Big(X_{4it} \Delta X_{zit} + \Delta X_{4it} X_{zit} - \Delta X_{4it} \Delta X_{zit} \Big)$$

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