ENVIRONMENTAL QUALITY AND INCOME DYNAMICS: WHAT DOES THE GLOBAL EVIDENCE TELL US?

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Abstract

This paper analyzes the evolution of two major determinants of social welfare, namely income and environmental quality. In particular, by using a distribution dynamics approach based on Markov chains for 126 countries over the period 1970 to 2006, we investigate the shape and the behavior of the joint distribution of per capita income and pollution as well as the mobility of countries within this distribution. Our study shows that a country's income level does matter for pollution dynamics, as its present level of development affects its future pollution status. Indeed, we find a strong long-run negative relationship between income and environmental quality, implying that, whenever it is observed, the Environmental Kuznets Curve is a transitory phenomenon. According to our findings, two separate traps emerge: a poverty trap (low-income/low-pollution) and an environment trap (high-income/high-pollution). This allows us to validate only part of the theoretical literature predicting the existence of multiple equilibria in the space environment-income.

JEL codes: C14, O11, O44, Q53

Keywords: Markov Chains, Air Pollution, Economic Development, Multiple Equilibria

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1. Introduction

Pollution is widely recognized to negatively affect health and social welfare. For this reason, public intervention as well as international coordination are developing in order to combat air pollution[1]. The pollution–economic growth relation has captured the attention of policymakers, theorists and empirical researchers alike, especially in the last two decades. So far, empirics have failed to reach conclusive results. This work contributes to the current debate by investigating nonlinearities in the dynamic interaction between income and pollution.

By considering a sample of 126 countries, Figures 1 and 2 below present the estimated joint distributions of income and pollution (using GDP per capita and CO_2 emissions) in 1970 and 2006, respectively.[2] By comparing the initial distribution with the final distribution, we observe the emergence of a second peak characterized by higher income and pollution levels. This suggests that throughout the course of time we could end up with multiple steady-states. This evidence motivates our study.

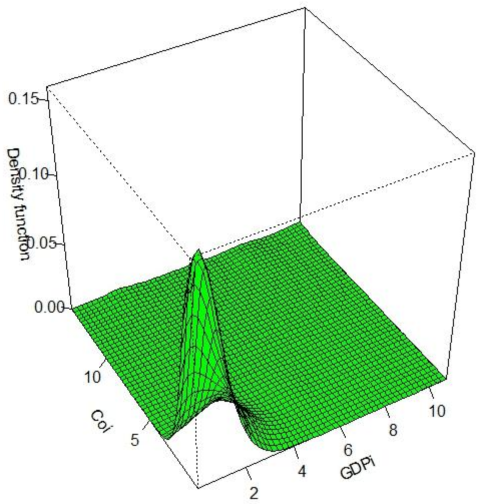

Figure 1: Initial distribution (1970)

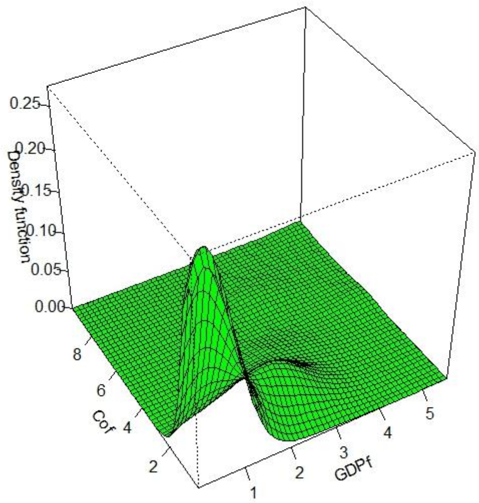

Figure 2: Final distribution (2006)

This work fills a gap in the environment-growth literature as it examines simultaneously both income and pollution dynamics. Specifically, we analyze the shape and behavior of the joint distribution of per capita income and pollution as well as the mobility of countries within this distribution. To do so, we employ nonparametric techniques, namely stochastic kernels and Markov chains, since cross-section and panel data econometric techniques, which study the behavior of the

[1] For example see Obama's Speech (State of The Union, 2010) and United Nations Framework Convention on Climate Change 'Kyoto Protocol' (1997).

[2] These distributions are estimated by using two smooth kernel functions centered over each observation and are based on a nonparametric method provided by Bowman and Azzalini (1997). See Appendix A for a detailed description of the relevant method.

"average" economy, are not suitable. Our study makes a contribution in the environment –pollution nexus in several important ways. First, by taking an agnostic view on *equilibrium multiplicity* vs. *uniqueness*, our methodology allows us to uncover the validity of theoretical models predicting poverty and/or environment traps (John and Pechennino, 1994; Xepapadeas, 1997; Mariani et al., 2010). Second, our framework enables us to reveal divergence/convergence trends using a world sample. Third, we introduce a novel definition of the state-space, which includes jointly income and pollution.[3]. Finally, we conduct inferences on the relationship between the development stage and pollution dynamics of countries, in order to draw policy implications.

We arrive at several conclusions. First, our results show a long-run strong negative relationship between income and environment quality. We predict that at the end of the dynamic process the world will be divided into two main groups: countries with low-income/low-pollution and high-income/high-pollution. In other words, our results do not validate models in which countries can be trapped in a poverty-environment trap. Steady-state predictions reveal that around 63% of countries will be characterized by a high-pollution (i.e., yearly per capita CO_2 emissions higher than 2.34 metric tons) if our consumption-production behavior remains unaltered. Second, a country's income level does matter for its pollution dynamics, since its current development stage influences its future pollution prospect. Finally, the convergence process towards the steady-state is very slow. This finding gives citizens and policy makers a limited time window to take action and return to a sustainable development path.

The rest of the article is structured as follows. In Section 2, we relate our contribution with the existing literature. In Section 3, we present the dataset and the empirical methodology employed in this work. In Section 4, we estimate the transition probabilities between states in the income-pollution state-space and the steady-state distributions of countries with regard to the above variables. Finally, we compute some mobility indices showing the frequency of transitions between states. In Section 5, we provide some concluding remarks and policy implications. The Appendices include details of the empirical analysis.

2. Related Literature

2.1 Theoretical Literature

The theoretical framework of our paper comprises the literature on poverty and environmental traps, i.e. situations in which countries remain persistently trapped into low-income and/or low-environment quality. According to the literature, poverty traps may arise when there are strong externalities and strategic complementarities affecting an economic system. An early work is

[3] See Fiaschi and Lavezzi (2003, 2007) for similar works on the relationship between income levels and growth rates.

by John and Pechennino (1994) who study the relation between growth and environmental quality in an OLG model where short-lived agents make decisions on capital and environment quality accumulation with long-lasting impact on factor productivity and the environment. Their model exhibits a case where economies with sufficient capital and environment quality experience growth and improving environment quality, while economies with worse initial conditions converge towards a low-capital, low-environment quality equilibrium, despite increasing returns to production. Xepapadeas (1997) analyzes an endogenous growth model with productive and abatement capital as well as increasing returns due to knowledge spillovers in production and pollution abatement. He shows that countries with environmental concerns can be trapped in a low-growth, high-pollution equilibrium because of insufficient knowledge of pollution abatement. Mäler et al. (2003) analyze a Solow-type model with emissions flow as a production input and nonlinear feedbacks in the environmental system. They demonstrate the possibility of locally stable equilibria with low-capital, low-pollution stocks and high-capital, high-pollution stocks; the steady-state where the economy ends up depends on the degree of pollution decay and the size of the emissions flow.

Ikefuji and Horii (2007) investigate the link between poverty and environmental degradation in an OLG model with agent heterogeneity, environmental externalities, human capital accumulation and credit constraints. They assume that environmental quality influences labour productivity and wealth dynamics through agents' ability, while wealth distribution determines if agents rely on primitive technology that reduces environmental quality. This interaction may lead an economy to a "poverty-environment trap" where lower environmental quality lowers income and the education level, which, in turn, accelerates environmental degradation. Mariani et al. (2010) develop an OLG model with human and physical capital, with two-sided feedback between life expectancy and environmental quality. They show that countries starting from low enough environment quality and human capital will be caught in a low-life expectancy, low-environmental quality, low-human capital trap. D'Alessandro et al. (2010) analyze a model with perfect complementarity between capital and energy, two perfectly substitutable energy sources (fossil fuels and alternative energy), and harnessed energy given by past accumulation in alternative energy sources capacity (AESC). They show that economies will be trapped in low-income, low environmental quality steady-states if the share and productivity of investments in AESC are too low to increase energy availability and the energy-harnessing capacity is small.

Naimzada and Sodini (2010) examine the dynamics of an OLG model with environment, a CES production function and agents who invest in environment, taking the actions of other agents of the same generation as given. The authors show the possibility of a high-income, low-environment steady-state when TFP increases over a threshold value and the elasticity of substitution between capital and labour is sufficiently lower. Finally, Varvarigos (2010) studies a model where: (a) longevity is positively affected by public health spending and negatively influenced by pollution, (b) environmental degradation is positively influenced by pollution due to production and it is mitigated by public environment expenditure. He proves that low income-low pollution equilibria are possible depending on the elasticities of: a) environmental damage with regard to pollution; b) environmental improvements with respect to abatement policy; c) output wrt capital; and d) output wrt the average capital-labour ratio. The likelihood of traps is also a function of the cleanliness of production technology, TFP and the initial conditions.

2.2 Empirical Literature

Markov chains have been used to study income dynamics. In a seminal work, considering 118 countries observed for the period 1962 to 1985, Quah (1993) uncovers a tendency towards a world divided into rich and poor countries, where escaping from the poverty trap is a low probability event. Fiaschi and Lavezzi (2003, 2007), considering around 120 countries observed for the periods 1960 to 1989 and 1950 to 1998, respectively, show that GDP growth first declines, then accelerates and eventually falls as per capita income rises following a nonlinear path.[4]

Our work is also related to numerous attempts to explain the pollution-growth nexus. Most studies test the validity of the so called Environmental Kuznets Curve (EKC hereafter) hypothesis, which postulates an inverted U-shaped relationship between environmental degradation and income growth (see Grossman and Krueger, 1994 and 1995). Although numerous studies test the EKC hypothesis, for individual countries[5] and panels of countries,[6] empirics have failed to yield conclusive results Aslanidis (2009); Soyas and Sari (2009)).[7] Moreover, most empirical studies are considered to be econometrically weak (Stern, 2004; Narayan and Narayan, 2010; Brock and Taylor, 2010). In a recent study, Narayan and Narayan (2010) examine the EKC hypothesis in a panel of 43 developing countries using panel co-integration in order to overcome econometric pitfalls. They conclude that CO_2 emissions fall as income rises only in Middle Eastern and South Asian countries. Finally, Brock and Taylor (2010) employ the Green Solow model as an alternative framework and present robust evidence of convergence between the 173 countries examined using

[4] Markov chains analysis have been also used to study regional convergence, i.e. Fingleton (1997, 1999), Lopez-Bazo et al. (1999), Chesire and Magrini (2000), Mossi et al. (2003) Le Gallo (2004) and Geppert and Stephan (2008)

[5] See, among others, Friedl and Getzner (2003), Roca et al. (2001), De Bruyn et al. (1998) and Roberts and Grimes (1997).

[6] See, Canas et al. (2003), Stern (2004) Perman and Stern (2003), Huang and Lin (2007) among others.

[7] For an extensive survey on the studies which tested the economic growth-environmental pollution nexus and the EKC hypothesis see, among others, Stern (2004); Coondoo and Dinda (2002); Dinda (2004); Luzzati and Orsini (2009) and Halicioglu (2009).

standard panel techniques.

In a parallel strand of research, environmental convergence (using CO_2 emissions) is examined. In a recent work, Bulte et al. (2007) argue that income convergence leads to pollutant emissions convergence. Overall, findings on environmental convergence alone are contradictory, as a number of scholars support the hypothesis of convergence in CO_2 emissions per capita (see Strazicich and List (2003), Romero-Avila (2008) and Westerlund and Basher (2008)), whereas others provide evidence of divergence (see, e.g., Nguyen-Van (2005), Barassi et al. (2008)). Finally, in a study related to our work, Aldy (2006) shows that Markov chain analysis does not provide convincing evidence on future emissions convergence. The author finds evidence of convergence among 23 OECD countries, whereas emissions appear to be diverging for a global sample composed of 88 countries for 1960–2000.

Overall, our results confirm the existence of multiple steady-states. Specifically, two separate traps emerge: a poverty trap (low-income, low-pollution) and an environment trap (high-income, high-pollution), which is in line with only part of the theoretical literature outlined in the previous sub-section (Mäler et al., 2003, Naimzada and Sodini, 2010, Varvarigos, 2010). Also, our estimates reveal that the interaction between income and pollution slows down the convergence process, compared to e.g. Fiaschi and Lavezzi (2003, 2007).

3. Data and Methodology

3.1 Data

Our sample consists of cross-country panel data, for income and pollution. As Markov chain analysis requires long time series together with a large number of cross-sections, we employ GDP per capita (at 2005 constant prices) and CO_2 emissions (metric tons per capita) originating from Penn World Tables (version 6.3) and UN's World Development Indicators, respectively. Variables are expressed in relative terms. In particular, following the literature on Markov Chains, we apply a mean normalization. Two samples were employed. The main sample considers 126 countries for the 1970-2006 period. The second sample, used for robustness check, considers 95 countries for the 1960-2006 period.[8] As a proxy for pollution, we decided to use CO_2 emissions for three reasons. First, carbon dioxide is one of the main components of the greenhouse gas emissions in the atmosphere, that is, gases that absorb and emit radiations within the thermal infrared range. Second, CO_2 emissions are available for a long period of time and for many countries.[9] Finally, in this way,

[8] The 1970-2006 sample contains about 200 observations more than the 1960-2006 one and, given the greater number of countries, it allows us to generalize our conclusions. Appendix B provides the country lists for both samples.

[9] We would have been keen to include alternative indicators of air or water pollution such as PM10, but unfortunately they are not available for a long period of time.

we can compare our results with the existing literature.

3.2 Estimating the Transition Matrix

We model the income-pollution dynamics as a discrete-time stochastic process, in which the evolution of each country follows a Markov chain stochastic process with a bivariate state-space. In general, a stochastic process is described by a *stochastic matrix* containing the *transition probabilities* from one state to another.[10] If the probability of moving from state i to state j in one period (p_{ij}) depends only on the current state i, the stochastic process is called a Markov chain. We assume that p_{ij} does not change over time, that is, we assume a time invariant Markov chain.[11] Therefore, the interpretation of our results will be conditioned on the *ceteris paribus* assumption. Given a certain state-space S, we have that $p_{ij} \in [0,1]$ and $\sum_{j=1}^{S} p_{ij} = 1, \forall i, j \in S$.

In this framework, following Norris (1997) and Fiaschi and Lavezzi (2003), a maximum likelihood method is used to estimate transition probabilities from one state to another. In particular, we estimate:

$$\hat{p}_{ij} = \frac{N_{ij}}{N_i}$$

where N_i is the number of countries in state i at the beginning of the transition period and N_{ij} is the number of countries that moved from state i to state j during the transition period. Now, from the Ergodic theorem of Markov chains, we know that: if $\boldsymbol{P}$ is the transition matrix of a regular Markov chain (aperiodic and irreducible), and if $\boldsymbol{P^T}$ approaches a unique limiting matrix, then the process will reach a steady state distribution $p(T) = p(T+k) = p(0)P^T$, with $k = 1,2,...$.

The stationary distribution is also known as *ergodic distribution* and it does not depend on the initial distribution *p(0)*. The ergodic distribution captures the final distribution of countries with respect to pollution and income if the structure of the stochastic process is stable. In our case, the shape of the ergodic distribution provides a test of theories on poverty and environmental traps outlined in Section 2.1 of the paper.

3.3 Sample Splitting

States of the world are determined jointly by the income and pollution levels. Unfortunately,

[10] A key property of a stochastic matrix is that it has a *principal left eigenvector* corresponding to its largest eigenvalue, which is 1 (Norris, 1997).
[11] We will test this assumption later in the text.

the results of a Markov chain analysis may change significantly when we change the definition of the states.[12] In order to avoid this problem, following Fiaschi and Lavezzi (2003, 2007), we test our transition probability estimates by using a stochastic kernel to estimate the CO_2 dynamics for each GDP class in a continuous space.

The benchmark state-space is given in Table 1. By using the contour plot representation of Figure 1, that is, the Bowman and Azzalini (1997) technique described in Appendix A, we divide the observed data into three GDP classes and three CO_2 classes.[13] According to our classification, 40% of countries lie in the low GDP class, 30% in the middle GDP class and the remaining 30% in the high GDP class. This selection of the intervals provides us with roughly equal-size classes, as in Quah (1993).

Table 1: State-space

Income\CO_2 emissions	Low $< 0.2\mu_{CO2}$	Middle $[0.2\mu_{CO2}, 0.5\mu_{CO2})$	High $\geq 0.5\mu_{CO2}$
Low $< 0.4\mu_{GDP}$	S_1	S_2	S_3
Middle $[0.4\mu_{GDP,}\ 1\mu_{GDP}]$	S_4	S_5	S_6
High $\geq 1\mu_{GDP}$	S_7	S_8	S_9

For CO_2 emissions, 47% of the countries have low pollution (almost all low GDP countries), 34% of countries have high pollution (26% of these come from high-income countries and another 7% from middle-income countries) and only 19% of the sample is characterized by middle-pollution level (mainly middle-income countries). This division is consistent with the existence of a strong positive correlation between per capita GDP and CO_2 emissions. Fortunately, Markov chains enable a simple, complete probabilistic description of the system. However, the existence of this strong, positive correlation between per capita GDP and air pollution implies that most sample splitting techniques result in no observation in some states of the world (low-income/high-pollution and high-income/low-pollution). In this case, we cannot determine the *ergodic distribution*, given the indeterminacy of some transition probabilities.

To control for such possible complications, we change the definition of the states and use a partially different dataset (i.e. less countries and a longer time span) that allow us to verify the robustness of our results. By using the same technique as in Table 1, we split the distribution of countries in 1960 obtaining the state-space described in Table 2.

[12] Quah (1997), Bulli (2001) and Reichlin, (1999) argue that the process of discretizing the state-space of a continuous variable is necessarily arbitrary and can alter the probabilistic properties of the data.

[13] The thresholds which define the country classes are 40%, 100% of the sample average for GDP per capita and 20%, 50% of the sample average for CO_2 emissions.

Table 2: State-space as a robust check

Income\CO_2 emissions	Low $< 0.1\mu_{CO2}$	Middle $[0.1\mu_{CO2}, 0.5\mu_{CO2})$	High $\geq 0.5\mu_{CO2}$
Low $< 0.3\mu_{GDP}$	S_1	S_2	S_3
Middle $[0.3\mu_{GDP}, 0.85\mu_{GDP}]$	S_4	S_5	S_6
High $\geq 0.85\mu_{GDP}$	S_7	S_8	S_9

In the next section, we show that in terms of number and position of peaks, our results are robust to different specifications of the state-space.

4. Results

4.1 Transitional Dynamics

The dynamics of countries with respect to relative per capita income and pollution are represented by the transition matrix reported in Table 3. The first column reports the number of observations for every state. For example, state S_7 has only 7 observations; however, a steady state exists.[14] The main diagonal represents the probabilities that countries will remain in the same state after one year. Along the main diagonal, we can identify three, 3x3 blocks representing the transition process within each GDP class.

In the first block, we have the transition process of countries that will remain in the low-income class in the next period. Countries with low-income/low-pollution have a 99% probability to remain poor in the next period. This probability decreases to 96% for countries with middle-pollution and 93% for countries with high-pollution. For poor countries, it is impossible to move directly into the high GDP class. Countries with low-income/high-pollution (S_3) have more chances of becoming cleaner (9%) than richer (6.4%). Nonetheless, we note that countries in state S_3 have the highest probability to escape from poverty, compared to countries in states S_1 and S_2. Therefore, state S_1 is a candidate to be an attractor. Indeed, according to the ergodic distribution estimates, S_1 takes a relatively high value in the steady-state (20.1%).

[14] The ergodic distribution can be characterized by some states with zero mass. This happens when there exists only one irreducible closed set of positive persistent aperiodic states, and the remaining states are transient (see, e.g., Isaacson and Madsen, 1976, p. 74).

Table 3: Transition matrix for 1970-2006 over the state-space of Table 1

Obs	States	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
1553	S_1	**0.979**	**0.013**	**0**	0.007	0.001	0	0	0	0
170	S_2	**0.076**	**0.835**	**0.053**	0	0.035	0	0	0	0
78	S_3	**0**	**0.090**	**0.846**	0	0	0.064	0	0	0
220	S_4	0.064	0	0	**0.836**	**0.091**	**0**	0	0.009	0
519	S_5	0	0.012	0	**0.023**	**0.913**	**0.040**	0	0.012	0
486	S_6	0	0	0.010	**0**	**0.029**	**0.916**	0	0	0.045
7	S_7	0	0	0	0.143	0	0	**0.571**	**0.286**	**0**
60	S_8	0	0	0	0	0.067	0.017	**0.017**	**0.783**	**0.117**
1317	S_9	0	0	0	0	0.008	0.015	**0**	**0.008**	**0.983**
Ergodic dist.		0.201	0.035	0.022	0.023	0.099	0.149	0.00	0.008	0.462

Moving to the second block (middle-income countries), we can see that transition economies with low pollution have a 6.4% probability to move back to low GDP and low pollution and a 9.1% probability to increase their pollution level during one period. Middle-income countries with middle-pollution levels (S_5), have the same probability (1.2%) to move up or down the GDP ladder remaining at the same pollution level (S_2 and S_8). In addition, they exhibit a 4% probability to become more polluted versus a 2.3% probability to reduce their pollution level. Finally, even middle-income/high-pollution countries (S_6) tend to remain in the initial state, with only a 4.5% probability to move into the highest GDP class (S_9) and, a 1% chance to move into the lowest GDP class (S_3). For these countries (S_6), the probability to reduce their pollution is around 3%. According to the estimated ergodic distribution, at the end of the transition process, most middle income countries will be characterized by high pollution levels (14.9%). Overall, in this group there is a tendency toward middle and high pollution (24.8%) compared to low pollution (2.3%).

The last block corresponds to countries with high income. In this class, the highest mobility is observed in the less polluted countries (57.1%), but this is just because they are a few. Countries with middle pollution (S_8) have an 8.4% probability to fall into the middle-income class and an 11.7% probability to experience an increase in their pollution levels. However, countries that move from the high-income class to the middle-income class tend to reduce their emissions (6.7% of these countries move to state S_5, whereas only a 1.7% of them move to state S_6). Highly polluted and rich countries (S_9), typically the most advanced ones, have more than a 98% of probability to remain in the initial situation, with a 1.5% probability to experience a significant reduction in the income level. The tendency for high income countries to grow is confirmed by the ergodic distribution, with 46.2% of countries in the highest income class. Unfortunately, this growth also implies serious environmental damages.

Comparing the transition probabilities between states, we can roughly identify the most likely development paths. Diagram 1 shows the path that a typical country tends to have during its development process, if it does not remain in its initial (persistent) state. So, if a country starts from a low-income/low-pollution situation, S_1, it is more likely that it will experience first an increase in pollution, moving to state S_2 and then after to S_3 than moving to S_4. Once a country is characterized by low-income/high-pollution, S_3, it is most likely to end up in a final state such as S_6 (middle-income/high-pollution) or S_9 (high-income/high-pollution). Overall, an initially poor and low-polluting country will possibly experience initially a rise in its pollution level and subsequently will end up in the high (or middle) income class. From the ergodic distribution, we can see that S_1, S_6 and S_9 are final attractors. We will further discuss the characteristics of the stationary distribution in the next section. Notice that studies based only on GDP or CO_2 dynamics cannot make inferences about vertical or horizontal movements, respectively, while our approach allows us to distinguish between these movements as well as shed some light on their sequence.

Diagram 1: Typical development paths

CO_2 Emissions	High	S_3	S_6	S_9
	Middle	S_2	S_5	S_8
	Low	S_1	S_4	S_7
		Low	Middle	High
		Per-capita GDP		

Given the problems that might arise from the discretization of the state-space, we use stochastic kernel to represent the CO_2 dynamics for each GDP class in a continuous state-space. Our results are reported in Figures 3, 4 and 5. These figures correspond to the three blocks we discussed above when the state-space is continuous. On the vertical axis, we have the current value of CO_2 emissions and on the horizontal axis we have the estimated value for the next period. Therefore, these figures represent a phase diagram for CO_2 emissions. This means that on the 45-degree line we find all countries that will remain at exactly the same pollution level after one period. Above the 45-degree line, there are countries that will exhibit a reduction in pollution, while below we have countries that will experience an increase in CO_2 emissions. As illustrated in Figure 3, a high proportion of countries lies on the 45-degree line, meaning that they tend to remain at almost the same pollution level after one period. Nonetheless, all the countries that lie above the 45 degree line will move back to a lower pollution situation. Figure 3 shows that low-income countries have a relatively high volatility in terms of pollution levels, however, their emissions are always below 0.10 the world average. Relative to Figure 3, Figures 4 and 5 show that middle- and high-income countries present a more homogeneous and stable behavior in terms of their pollution dynamics.

Figures 3, 4 and 5 are consistent with the transition matrix presented in Table 3. Moreover, since our contour plots never overlap, we can conclude that the thresholds identified for the sample splitting are sensible.

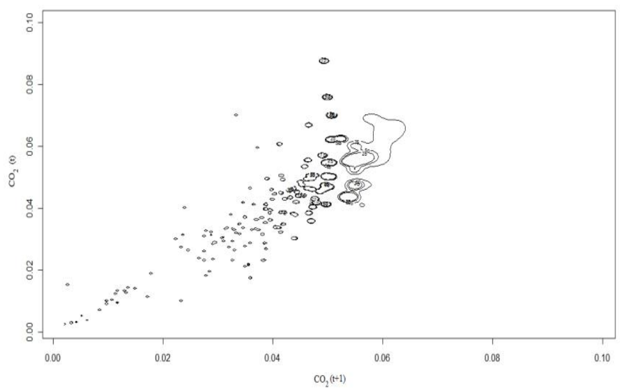

Figure 3: Stochastic kernel for Low income countries

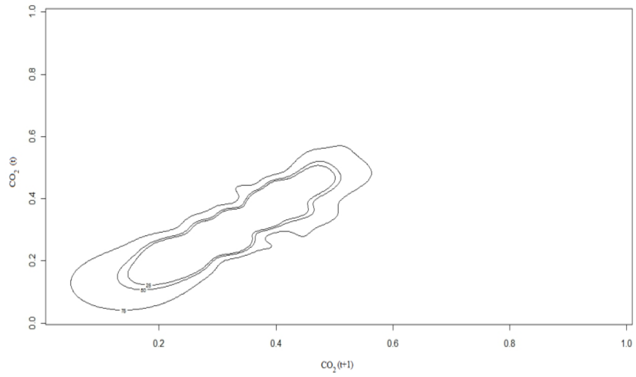

Figure 4: Stochastic kernel for Middle income countries

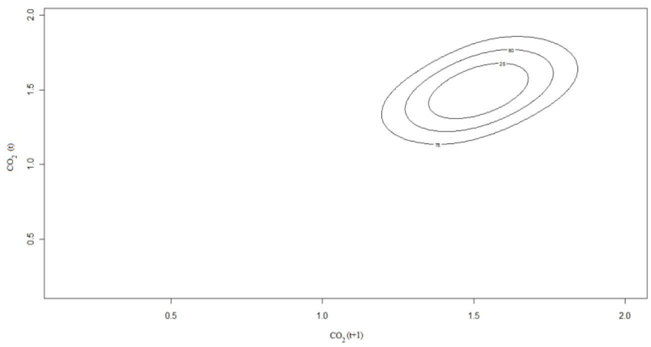

Figure 5: Stochastic kernel for High income countries

To validate the hypothesis concerning the stationarity of the transition matrix (see Section 3.2), we use the likelihood ratio test suggested by Anderson and Goodman (1957). As in López-Bazo et al. (1999), Neven and Gouyette (1995) and Le Gallo (2004), we divide the sample into two subsamples (1970-1987 and 1988-2006) and then compute the following statistic:

$$Q = -2\prod_{t=1}^{2}\prod_{i,j=1}^{9}\left(\frac{\hat{p}_{ij}}{\tilde{p}_{ij}(t)}\right)^{N_{ij}(t)}$$

where $\tilde{p}_{ij}(t)$ is the transition probability for subsamples *t=1* and *t=2.* As shown by Anderson and Goodman (1957), the Q-statistic is distributed as χ^2 with $S(S-1)$ degrees of freedom. The value of Q is 48.76, thus we do not reject the stationarity hypothesis of the transition matrix at a significance level α= 5%.

Additionally, we conducted some inferential tests on the transition matrix.[15] We do so in order to further explore the income-pollution relationship and shed light on country dynamics with respect to their GDP/CO_2 classes. According to Table 1C (available in Appendix C), we reject the hypothesis that all GDP classes are equally likely to end up with high pollution if they start from a state of middle-pollution (hypothesis (a)). In other words, the income class of a country does matter regarding their movement from the middle to the high-pollution class. In addition, we do not reject the hypothesis that highly polluting countries have the same probability to experience high pollution in the future, independently of their income class (hypothesis (b)). So, high pollution is equally persistent in all GDP classes. Regarding all GDP classes, we reject the hypotheses that the probability of countries remaining highly polluting is the same as the probability to fall into the other pollution classes (hypothesis (c_1) and (c_2)). Since the transition matrix depends on the state-space definition, we reject the null hypotheses at the 0.10 level.

At the same time, according to Table 2C (available in the Appendix C), for both middle- and high-income countries, we cannot reject the hypothesis that the probability of experiencing middle pollution is the same as the probability of high pollution ((hypothesis (d)). The remaining probabilities to fall into a high-pollution state differ from the probabilities to fall into low or middle-pollution states, starting from any initial state. Finally, we reject the hypothesis that, for each GDP class, the probabilities to fall into a high-pollution state is the same as the probabilities to fall into the middle or the low-pollution state ((hypothesis (e)).

4.2 Steady-state and Robustness

Table 4 reports the cross-country distribution of the first and last years of our sample, along with the ergodic distribution, in terms of the states defined above (see Section 3.3.). We can identify two main long-run equilibria: (i) low-income/low-pollution (S_1) and, (ii) high-income/high-pollution (S_9). The ergodic distribution shows that around 63% and 22% of the world's countries will be characterized by high and low-pollution levels respectively, if our consumption-production habits remain the same. Moreover, Table 4 gives an idea about how far the countries are from the stationary state. The convergence process seems to be quite slow. For instance, the fraction of countries with high income/high pollution levels has increased by 5% in 36 years and, the remaining distance from the steady state is approximately 15%.

[15] A detailed description of our inferential analyses is given in the Appendix C.

Table 4: Distributions over the state-space of Table 1

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
1970	0.365	0.032	0.008	0.111	0.111	0.071	0.016	0.024	0.262
2006	0.325	0.071	0.024	0.016	0.119	0.119	0.000	0.008	0.317
Ergodic	0.201	0.035	0.022	0.023	0.099	0.149	0.000	0.008	0.462

As a robustness check, Table 5 reports additional ergodic distributions obtained by changing the sample and the definition of the state-space. In this way, we can compare our previous results (Table 4) with the new results. The first row of the table contains the ergodic distribution derived by the new sample that consists of 95 countries for the 1960-2006 period. As before, we can identify two main equilibria, namely low-income/low-pollution and high-income/high-pollution. Furthermore, this row confirms the existence of a strong polarization of countries in the CO_2 dimension.

The last two rows of Table 5 provide another robustness check for our analysis. There, we re-estimate the ergodic distributions of our two samples by using the state-space defined in Table 2 (see Section 3.3). These two distributions are somewhat different with respect to the ergodic distributions based on the state-space defined in Table 1, but this is just because we have changed the state-space definition, lowering the thresholds in Table 2. Overall, we can argue that our conclusions remain qualitatively the same. Based on 1960-2006 sample the number of countries with high pollution increases from 40 (2006) to 64 out 95 the end of the convergence process. Likewise, based on 1970-2006 sample the number of countries with high pollution rises to 78 out 126 the end of the convergence process.[16]

Table 5: Robustness Check

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
Ergodic distribution from sample (1960-2006)									
(1960-2006)	0.279	0.028	0.002	0.069	0.117	0.097	0.003	0.016	0.388
Ergodic distributions over the state-space of Table 2									
(1970-2006)	0.111	0.025	0.025	0.009	0.085	0.189	0.000	0.006	0.549
(1960-2006)	0.142	0.016	0.001	0.028	0.114	0.145	0.001	0.019	0.534

By considering our main sample (1970-2006) and the state-space in Table 1, Table 6 shows the composition of each GDP class with regard to pollution in the stationary state. The majority of poor countries (78%) will be characterized by low pollution, 13.5% by middle pollution and only an 8.5% by high pollution. Moving to middle-income countries, 55% of these will be characterized by high pollution, 37% by middle pollution and 8.5% by low pollution. Finally, 98% of rich countries will be highly polluting countries. These findings confirm the presence of a strong negative relationship between income and environmental quality in the long run. Thus, our evidence does not

[16] By considering the normalized ergodic matrix, inference shows that we cannot reject the hypothesis of heteroskedasticity. All inference matrices are available upon request.

support the EKC hypothesis as a long-run phenomenon.

Table 6: Ergodic distribution of CO_2 emissions for each GDP class

	Low Pollution	Middle pollution	High Pollution
Low income	0.780	0.135	0.085
Middle income	0.085	0.367	0.548
High Income	0.001	0.018	0.982

We estimate the speed of the convergence process by using the concept of *asymptotic half-life*, i.e. the time required to cover half of the distance from the ergodic distribution. The asymptotic half-life is:

$$h = -\frac{\log 2}{\log|\lambda_2|}$$

where, λ_2 is the second largest eigenvalue of the transition matrix (see Fiaschi and Lavezzi, 2003). In our case, h= 79 periods, which implies a very slow speed of convergence. When the convergence period is so long, h becomes just a signal of low mobility across states instead of a real measure of convergence (additional measures of mobility are provided in the next section). Indeed, we cannot assume that transition dynamics will remain the same for 160 years, the time required for complete convergence to the ergodic distribution. Fiaschi and Lavezzi (2003) find an asymptotic half-life of about 49 periods. Therefore, we can imagine that the divergent dynamics found by Aldy (2006) for CO_2 emissions further slows down the convergence process.

4.3 Mobility indices

We calculate some mobility indices that are useful in understanding how frequent the transitions from one state to another are. Following Bartholomew (1982), we initially consider two indices of mobility. These indices are defined over the interval [0,1] and measure the speed of convergence towards the ergodic distribution. Formally, we have:

$$I_1(P) = \frac{1}{N-1}\sum_i \sum_j p_i(T) p_{ij} |i-j|$$

$$I_2(P) = \frac{1}{(N-1)^2}\sum_i \sum_j p_i(T) p_{ij} (i-j)^2$$

As suggested by Fiaschi and Lavezzi (2005), two other indices can be useful in order to understand the mobility of countries during the transition process. These two indices are built on the same idea as the previous ones, but they only consider the transition probabilities:

$$I_3(P) = \frac{1}{A}\sum_i \sum_j p_{ij} |i-j|$$

$$I_4(P) = \frac{1}{A^2} \sum_i \sum_j p_{ij} (i-j)^2$$

where, A is a constant parameter used to normalize the indices to 1. Table 7 reports our results. As we can see, these results confirm our previous finding on the speed of convergence. That is, transitions are not so fast.

Table 7: Mobility indices

Indices	Values	Variance
I_1	0.033	7.01e-06
I_2	0.011	8.48e-07
I_3	0.111	6.33e-05
I_4	0.042	2.14e-05

Indices I_2 and I_4 give a higher weight to transitions between distant states in order to stress the importance of very significant changes in status. When we give a higher weight to transitions between distant states, mobility indices decrease in size, implying that significant jumps are not so frequent.

5. Conclusions

By taking an agnostic point of view on *equilibrium multiplicity* vs. *uniqueness*, this paper studies income and pollution dynamics, considering the behavior of their joint distribution. Using a Markov chain approach with a bi-variate state-space, our findings do not support theoretical models predicting that a country could be trapped at the same time in a poverty and in an environmental trap. This means that a stationary equilibrium with low-income is alternative to a stationary equilibrium with high-pollution. Thus, a strong long-run negative relationship between income and environmental quality emerges. This implies that, the Environmental Kuznets Curve should be considered as a transitory phenomenon instead of a persistent evidence. Moreover, our empirics demonstrate that most countries (63%) will be characterised by high pollution levels if our consumption-production habits remain the same. Regarding the transition process, the development level of a country affects pollution dynamics. In other words, the future pollution class of a country is sensitive to its current income status. We also find a very slow speed of convergence towards the steady-state. Thus, pollution slows down the convergence process.

Overall, our analysis is compatible with two supplementary hypotheses; that is governments do not invest enough in environment maintenance and effective pollution abatement technologies do not exist. Notice that public intervention and the existence of an effective abatement technology are crucial assumptions in the theoretical literature on poverty-environment traps.

Finally, since the world's population is expected to increase dramatically in the coming decades, per capita CO_2 emissions should be reduced substantially in order to avoid catastrophic consequences. This should be taken into account in the context of negotiations on climate change.

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APPENDICES

Appendix A: Estimating Density Functions

Instead of providing simple histograms -with the well known discretization problems- we replace them with smooth kernel functions centered over each observation. In particular, by using a nonparametric method provided by Bowman-Azzalini (1997), we estimate the density function $f(C_t, Y_t)$, where C_t is the pollution level at time *t* and Y_t is the per capita GDP at time t. Notice that we do not impose any restriction on the shape of $f(.,.)$, which is at least *a priori* unknown. The kernel estimator can be written as follows:

$$\hat{f}(C_t, Y_t) = \frac{1}{N}\sum_{i=1}^{N} k(C_t - C_{it}; h_C) k(Y_t - Y_{it}; k_Y),$$

where, (C_t, Y_t) represents the point at which the density is estimated, $\{C_{it}, Y_{it}; i = 1,..., N\}$ denote the data and (h_C, h_Y) are two joint smoothing parameters (or bandwidths). Alternatively, we could use a bivariate kernel with correlated components, but a product of univariate components is usually sufficient, especially for descriptive statistics. Functions $k(.,.)$ give weights that decrease monotonically as the difference between central points and observations increases. In particular, two univariate normal kernels, one for each explanatory variable, are used and *h* is obtained by minimizing the mean integrated squared error (MISE). The choice of the optimal smoothing parameter is relevant because, there is a trade-off between bias and variance of our estimates. In fact, whereas variance is decreasing in *h*, bias is increasing in *h*.

Appendix B: Country Lists

Table 1B: 1970-2006

Afghanistan	Gabon	Niger
Albania	Gambia, The	Nigeria
Algeria	Ghana	Norway
Angola	Greece	Pakistan
Antigua and Barbuda	Grenada	Panama
Argentina	Guatemala	Papua New Guinea
Australia	Guinea	Paraguay
Austria	Guinea-Bissau	Peru
Barbados	Guyana	Philippines
Belgium	Haiti	Poland
Belize	Honduras	Portugal
Benin	Hungary	Qatar
Bolivia	Iceland	Romania
Brazil	India	Rwanda
Brunei Darussalam	Indonesia	Sao Tome and Principe
Bulgaria	Iran, Islamic Rep.	Saudi Arabia
Burkina Faso	Iraq	Senegal
Cambodia	Ireland	Sierra Leone
Cameroon	Israel	Singapore
Canada	Italy	Solomon Islands
Central African Republic	Jamaica	South Africa
Chad	Japan	Spain
Chile	Jordan	Sri Lanka
China	Kenya	St. Lucia
Colombia	Korea, Rep.	St. Vincent & Grenadines
Congo, Dem. Rep.	Lao PDR	Sudan
Congo, Rep.	Lebanon	Suriname
Costa Rica	Liberia	Sweden
Cote d'Ivoire	Libya	Switzerland
Cuba	Luxembourg	Thailand
Cyprus	Macao SAR, China	Togo
Denmark	Madagascar	Trinidad and Tobago
Djibouti	Mali	Tunisia
Dominica	Mauritania	Turkey
Dominican Republic	Mauritius	Uganda
Ecuador	Mexico	United Arab Emirates
Egypt, Arab Rep.	Mongolia	United Kingdom
El Salvador	Morocco	United States
Equatorial Guinea	Mozambique	Uruguay
Ethiopia	Nepal	Venezuela, RB
Fiji	Netherlands	
Finland	New Zealand	
France	Nicaragua	

Table 2B: 1960-2006

Algeria	India	Switzerland
Argentina	Indonesia	Thailand
Australia	Iran	Togo
Austria	Ireland	Trinidad &Tobago
Barbados	Israel	Tunisia
Belgium	Italy	Turkey
Benin	Jamaica	Uganda
Bolivia	Japan	United Kingdom
Brazil	Jordan	United States
Burkina Faso	Kenya	Uruguay
Cameroon	Korea, Republic	Venezuela
Canada	Luxembourg	
Central African Repu	Madagascar	
Chad	Mali	
Chile	Mauritania	
China	Mauritius	
Colombia	Mexico	
Congo, Dem. Rep.	Morocco	
Congo, Republic of	Mozambique	
Costa Rica	Nepal	
Cote d`Ivoire	Netherlands	
Cyprus	New Zealand	
Denmark	Nicaragua	
Dominican Republic	Niger	
Ecuador	Nigeria	
Egypt	Norway	
El Salvador	Pakistan	
Equatorial Guinea	Panama	
Ethiopia	Papua New Guinea	
Fiji	Paraguay	
Finland	Peru	
France	Philippines	
Gabon	Portugal	
Gambia, The	Romania	
Ghana	Rwanda	
Greece	Senegal	
Guatemala	Sierra Leone	
Guinea	Singapore	
Guinea-Bissau	South Africa	
Haiti	Spain	
Honduras	Sri Lanka	
Iceland	Sweden	

Appendix C: Hypothesis Testing

This section presents the inferential analysis we conduct on the transition matrix. For regular Markov chains, the difference between the elements of the transition probabilities after a number of transitions tends to zero. In other words, all elements of all columns tend towards a common limit as the number of transitions increases. At the same time, Stuart and Ord (1994) show that each row of the transition matrix converges to a N-variate normal distribution, that is, $\sqrt{N_i}(\hat{p}_{ij} - p_{ij})$ asymptotically converges towards a normal distribution with zero mean and variance $p_{ij}(1-p_{ij})$. We can use this result to conduct inference on the elements of the transition matrix. By using a standard normal distribution, we can compare elements of the same row as follows:

$$s^2 = \frac{N_i(\hat{p}_{ij} - \hat{p}_{iq})^2}{\hat{\sigma}_{ij}^2 + \hat{\sigma}_{iq}^2 + 2N_i \hat{p}_{ij}\hat{p}_{iq}}$$

where s^2 is the sample variance, N_i is the number of observations in row *i*, *j* and *q* are two general states at the end of the period, $\hat{p}$ are the estimated probabilities and $\hat{\sigma}^2$ are the estimated variances.

Similarly, we can compare elements of different rows (i and z)

$$s^2 = \frac{N_i N_z (\hat{p}_{ij} - p_{zq})^2}{N_z \hat{\sigma}_{ij}^2 + N_i \hat{\sigma}_{zq}^2}.$$

Given these results, we test specific hypotheses concerning the transitional dynamics. Under the assumption that rows of transition matrix are independent, we run the following p-value tests.

Tests

a. *Is pollution equally increasing among GDP classes*? We test whether low and high-income countries have the same probability of middle-income countries to move from the middle to high-pollution status.

For low-income countries $H_0 : p_{53} + p_{56} + p_{59} = p_{23} + p_{26} + p_{29}$

For high-income countries $H_0 : p_{53} + p_{56} + p_{59} = p_{83} + p_{86} + p_{89}$

b. *Is high pollution equally persistent among GDP classes*? We test if the probability of occurrence of high pollution is the same across GDP classes. To do this, we compare middle-income countries with low and high-income countries respectively with regard to pollution.

For low-income countries $H_0 : p_{63} + p_{66} + p_{69} = p_{33} + p_{36} + p_{39}$

For high-income countries $H_0 : p_{63} + p_{66} + p_{69} = p_{93} + p_{96} + p_{99}$

c. *Does a country tend to remain in the high-pollution class*? We investigate whether high pollution is persistent in each GDP class. That is, we conduct the following set of tests:

For low-income countries $H_0 : p_{33} = p_{31}$ (c_1) *and* $H_0 : p_{33} = p_{32}$ (c_2)

For middle-income countries $H_0 : p_{66} = p_{64}$ (c_1) *and* $H_0 : p_{66} = p_{63}$ (c_2)

For high-income countries $H_0 : p_{99} = p_{97}$ (c_1) *and* $H_0 : p_{99} = p_{98}$ (c_2)

d. *Are transition probabilities symmetric with respect to pollution*? Starting from any given state, we want to know if countries have the same probability of going into a high-pollution class compared with low and middle-pollution classes. Then, for any GDP class we test the following hypotheses:

Low vs high pollution $H_0 : p_{.,3} + p_{.,6} + p_{.,9} = p_{.,1} + p_{.,4} + p_{.,7}$

Middle vs high pollution $H_0 : p_{.,3} + p_{.,6} + p_{.,9} = p_{.,2} + p_{.,5} + p_{.,8}$

e. *Is the probability to fall into a high-pollution class equal to the probability to fall into any other pollution class*?

Starting from any initial state, we want to know if countries have the same probability of moving into a high-pollution state relative to low and middle pollution states, given a final GDP class. So, we examine the following:

Probability of moving to S_3 vs S_1 $H_0 : p_{,3} = p_{,1}$

Probability of moving to S_3 vs S_2 $H_0 : p_{,3} = p_{,2}$

Probability of moving to S_6 vs S_4 $H_0 : p_{,6} = p_{,4}$

Probability of moving to S_6 vs S_5 $H_0 : p_{,6} = p_{,5}$

Probability of moving to S_9 vs S_7 $H_0 : p_{,9} = p_{,7}$

Probability of moving to S_9 vs S_8 $H_0 : p_{,9} = p_{,8}$

Table 1C: Tests of hypotheses a, b and c

Test hypothesis	**Low Income p-value**	**H_0**	**Middle Income p-value**	**H_0**	**High Income p-value**	**H_0**
a	0.4229	R	-	-	1	R
b	0.0163	NR***	-	-	0.0163	NR***
c_1	0.995	R	1	R	1	R
c_2	0.928	R	0.921	R	0.954	R

Notes: p-values measure the probability that H_0 is false. Significance levels: *** 2%, ** 5%, * 10%. R: reject, NR: not reject; **c_1**: probability to stay in high-pollution class compared with the probability to move in low-pollution class; **c_2**: probability to stay in high-pollution class compared with the probability to move in middle-pollution class.

Table 2C: Tests of hypotheses d and e

Income	**Test d**	**p-value**	**H_0**	**Test e**	**p-value**	**H_0**
Low	Low vs High pollution	1	R	S_3 vs S_1	1	R
Low	Middle vs High pollution	0.7528	R	S_3 vs S_2	1	R
Middle	Low vs High pollution	1	R	S_6 vs S_4	1	R
Middle	Middle vs High pollution	0	NR	S_6 vs S_5	1	R
High	Low vs High pollution	0.989	R	S_9 vs S_7	0.9989	R
High	Middle vs High pollution	0	NR	S_9 vs S_8	0.6081	R

Note: p-values measure the probability that H_0 is false. Significance levels: *** 2%, ** 5%, * 10%. R: reject, NR: not reject.