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THE BUILDING BLOCKS OF INTERNATIONAL ECOLOGICAL FOOTPRINT INEQUALITY: A REGRESSION-BASED DECOMPOSITION.

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ABSTRACT: This paper performs an empirical Decomposition of International Inequality in Ecological Footprint in order to quantify to what extent explanatory variables such as a country's affluence, economic structure, demographic characteristics, climate and technology contributed to international differences in terms of natural resource consumption during the period 1993-2007. We use a Regression-Based Inequality Decomposition approach. As a result, the methodology extends qualitatively the results obtained in standard environmental impact regressions as it comprehends further social dimensions of the Sustainable Development concept, i.e. equity *within* generations. The results obtained point to prioritizing policies that take into account both future and present generations.

Keywords: Ecological Footprint Inequality, Regression-Based Inequality Decomposition, Intragenerational equity, Sustainable development

1- INTRODUCTION

According to International Declarations from Stockholm (1972) to Rio de Janeiro (2012) Sustainable Development is a concept that relies on three main pillars: environmental, economic, and social. However the concept is often narrowed to the environmental pillar by one of its strongest arguments for protecting the environment: the ethical need for guaranteeing that future generations would continue to enjoy similar opportunities of leading worthwhile lives that are enjoyed by generations that precede them. This is indeed what comes to the mind of the vast majority of the population when they hear about Sustainable Development. Such inequality *between* generations in terms of natural resource consumption is thus universally perceived as inequitable, so that concern about future generations is clearly, in fact, a distributional concern. Nonetheless, such distributional concern may become a gross violation of such a Universalist principle associated with sustainability if we were obsessed about *inter*generational equity while neglecting a critical part of the social pillar, the *intra*generational equity (Anand and Sen, 2000). In this regard, as the Human Development Report (2011) argued, contemplating policies to restore sustainability independent of policies to address inequality among countries is equivalent to framing policies to address inequalities between certain groups (such as rural and urban) while neglecting the interrelationships with equity between other groups, such as poor and rich (UNDP 2011). This paper's main aim, thus, is to quantify to what extent the main drivers of natural resource demand explain the inequality in today's generations while taking into account the interrelationships with sustainable scale (inequality *between* generations)

It is widely known that several countries consume more natural resources than others do. One available indicator that measures such consumption is the Ecological Footprint (EF hereafter). The Global Footprint Network (Ewing et al., 2010) asserted that if everyone in the world in 2007 lived like an average resident of the USA or of the United Arab Emirates, more than 4.5 planet Earths would be required to support humanity's consumption rates. If instead the world were living like the average person in India, humanity would be using less than half the planet's biocapacity. Disentangling the causal determinants of this concrete global *intra*generational inequality will allow for the discussing and extending of some critical interactions that may occur involving equity *between* generations and equity *within* generations that should be considered for the achievement of both (UNDP, 2011; Neumayer, 2011). Hence, international environmental policies should not only urgently foster a more sustainable scale of the world economy, but also, at the same time, such policies should foster today's ecological equity. What ethical system can justify a concern about the well-being of those yet to be born, while not caring for the well-being of those alive today? (Daly and Farley, 2004). Furthermore, in some cases such policies may enjoy positive synergies which will reinforce both equities (Neumayer, 2011) and this paper provides some important clues along this line.

The study of driving forces behind the demand for natural resources (or pollution) has been of widespread interest to researchers and policy makers in recent decades because, in part, they align themselves with the vital and also widely spread concern for future generations. One common framework was suggested by Ehrlich and Holdren (Ehrlich & Holdren, 1971) who first proposed the so-called IPAT identity, where the environmental impact (I) is related to Population (P), Affluence (A) and Technology (T). Hence I=PAT. The strength of this identity stems from capturing the key driving forces of environmental impact. Further research developed this accounting equation into a stochastic regression model (York, et al., 2003). It allowed both for making test hypothesis and also introducing further factors that may have some influence to the environmental impact. As a result there is a vast knowledge about the driving forces of natural resource consumption (Caviglia-Harris et al., 2009; Dietz et al., 2007; Fischer-Kowalski and Amann, 2001; Rosa et al., 2004). These empirical analyses tell us about the effect (elasticity) that a rise in affluence, population or technology (or temperature or urban population share) would have to a particular environmental impact scale on natural resource demand. However, and this is the main contribution of the present paper, they do not reveal the effect these causal factors will have on the international environmental impact distribution, i.e. influence on *intra*generational inequality. Moreover, since natural resource scarcity is not a remote possibility anymore, distributional analysis on natural resource consumption may become more pressing to global governance. Accordingly, papers focused on how natural resources are distributed internationally are becoming of greater interest, and also becoming a hot topic in the literature: it is noticeable that empirical applications in this topic have risen significantly in recent years (Aubauer, 2011; Alcantara and Duro, 2004; Aldy, 2006; Dongjing et al. 2010; Duro and Padilla, 2006; 2008; 2011; Cantore, 2011; Ezcurra, 2007; Heil and Wodon, 1997; 2000; List, 1999; Brooks and Sethi, 1997; Miketa and Mulder, 2005; Nguyen Van, 2005; Padilla and Serrano, 2006; Strazicich and List, 2003; Steinberger et al., 2010; White, 2007; Wu and Xu, 2010; Teixidó-Figueras and Duro, 2012; Duro and Teixidó-Figueras, 2012 among others).

Methodologically, we go one step further in these two hot topics of ecological economics research by merging them: the ecological inequality measurement and the estimation of impact driving forces. To do so we perform the Inequality Regression-

Based-Decomposition (Fields, 2003) to disentangle the contributions of impact drivers to the asymmetries among countries in natural resource consumption (as measured by per capita EF). In doing so, we identify the underlying blocks of *intra*generational inequality in order deal with policy recommendations aimed at both sustainability and equity.

The remainder of this paper is organized as follows. Section 2 describes what Ecological Footprint is and provides some statistics related with its inequality measurement. Section 3 describes the methodology applied to decompose the inequality observed into the explanatory variables of the regression model used. Section 4 presents the results of the estimation of driving forces of the Ecological Footprint and its contribution to international inequality in the Ecological Footprint. Section 5 concludes the paper.

2- ECOLOGICAL FOOTPRINT INEQUALITY

The EF (Wackernagel and Rees, 1996) is one of the most comprehensive indicators of natural resource consumption currently available, the main advantage of which is its pedagogical strength: the land needed to maintain a country's consumption pattern. EF's units are measured in global hectares (gha hereafter), which are hectares with the world's average bio-productivity of six types of land: cropland, grazing land, forest land, carbon footprint, fishing grounds and built-up land[1]. More specifically, EF accounts for the biosphere regenerative capacity occupied by human activities via resource consumption (including household consumption as well as collective

[1] Any aggregate indicator will have both strengths and weaknesses (as is the case of measures of aggregate economic output), so that EF has been criticized as a measure to assess the sustainability level (see Fiala, 2008; van den Bergh & Verbruggen, 1999). However, EF is merely used here in resource consumption measurement as a proxy for natural capital. Furthermore, EF's strengths and weaknesses are now well known since it has benefited from academic scrutiny of its properties and limitations, allowing the interpretation of EF analyses in a transparent and unequivocal manner.

consumption such as schools, roads, fire brigades, etc.) and waste assimilation (mainly in terms of carbon emissions). Since both renewal resource provision and CO_2 emissions absorption depend highly on the health and integrity of ecosystems, regenerative capacity might be seen as a reliable proxy for the life-supporting capacity of natural capital (Monfreda et al., 2004). Consequently, the analysis of distribution of EF among countries may be read as the analysis of distribution of Natural Capital[2] as it approximates to an account of the main ecological functions of the environment (resource supply, waste disposal and life support).

In order to obtain a consumption-based indicator of the EF of any country, it is necessary to add the EF of imports (EF_I) and subtract the EF of exports (EF_E). In this way, we obtain the EF of consumption (EF_C): $EF_C=EF_P+EF_I-EF_E$. As a result, EF captures consumption in terms of land (and sea) regardless of *where* and *when* it is located: a country may be consuming either the land of other countries or the resources of future generations provided that Earth overshoot[3] occurs. Hence, there is a clear distributional content to what is captured by the EF index (Martinez-Alier, 2002). Analyzing its distribution encapsulates, in its very definition, unequal relations not only between countries, also between generations.

Table 1. World Ecological Footprint per capita

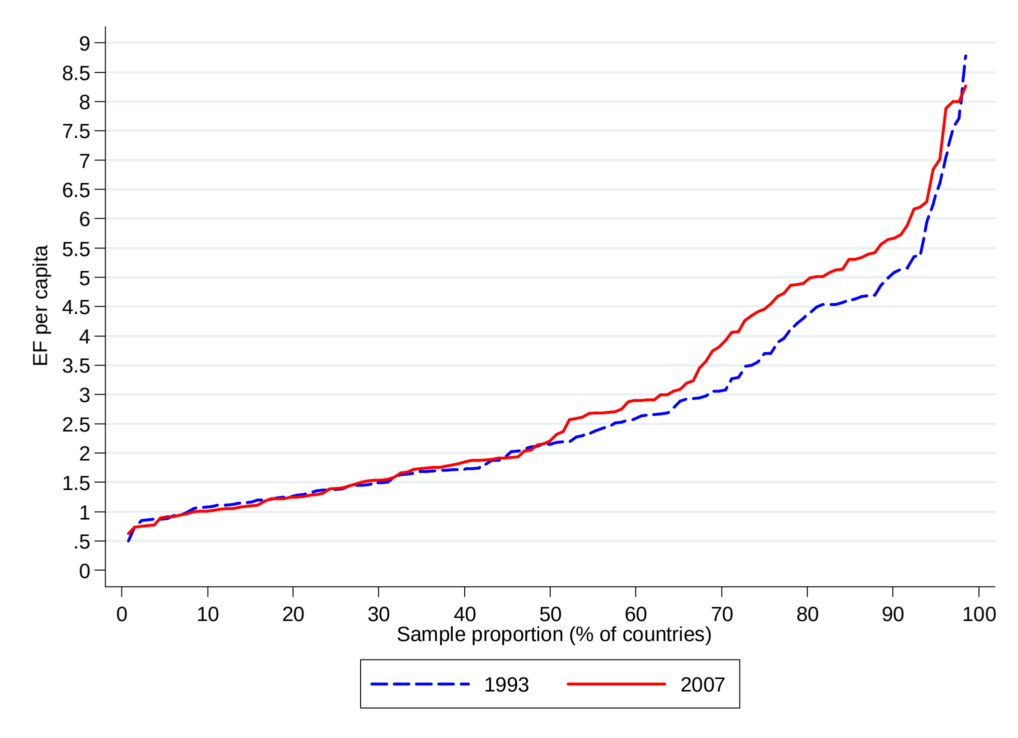
Year	EF (billion gha)	EF per capita
1993	14.35	2.59
1995	14.85	2.60
1997	15.12	2.57
1999	15.25	2.53
2001	15.54	2.51
2003	16.28	2.56
2005	17.29	2.66
2007	17.99	2.70

[2] See Ekins (2003) and Victor (1991) for Natural Capital discussions
[3] see Wackernagel et al., (2004)

In 2007 the human race's total Ecological Footprint worldwide was 18 billion *gha*. The population was 6.7 billion, so that the average Ecological Footprint per capita was 2.7*gha*. Nonetheless, according to Ecological Footprint National Atlas (Ewing et al., 2010), that year there were only 11.9 billion *gha* of biocapacity available (1.8*gha* per capita), which means that at least 6.1 billion of the *gha* consumed were charged to future generations[4]. Hence at least 33% of the EF per capita of the present generation was appropriated from future generations. On the other hand, neither were these *gha* consumed in an equitable way. Figure 1 is the Pen's Parade diagram of the distribution of EF per capita of 1993 and 2007. The Pen's Parade consists in ordering countries from low to high EF per capita so that in the horizontal axis we see the deciles and the vertical axis shows the EF per capita. It is easy to see that some countries had much greater EF per capita than others do. Besides, if we compare both years, we observe that the higher deciles significantly increased their EF per capita while the lower ones did not, actually slightly decreasing theirs. As a result, world EF per capita growth was mainly caused by higher deciles (table 1).

[4] In spite of the growing world population trend, the per capita EF has also been increasing each year, and since 1975, it has been consuming more Global Hectares each year than those available.

Figure 1: Pen's Parade Diagram of EF per capita for year 1993 and 2007

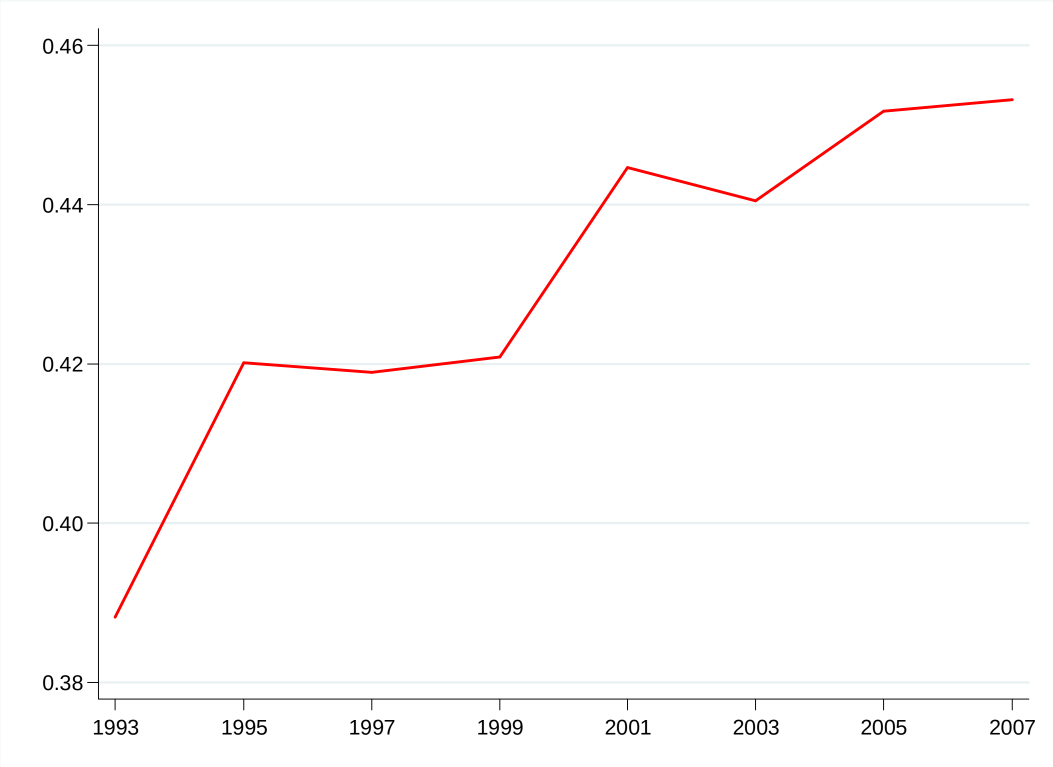


Note: own elaboration

This visual aid may give us a first intuition of the international inequality trend in terms of EF per capita. In this sense, figure 2 shows the EF inequality observed in the analyzed period according to the variance of logarithms[5] (var-log hereafter). According to this index, the inequality among countries increased, and so both the intergenerational equity (sustainability) and the *intra*generational equity became damaged. Regression based decomposition unravels which factors were the main drivers in the rise in EF per capita inequality and to what extent.

[5] In this work, inequality is measured by the Variance of Logarithms mainly because this index is methodologically linked to the Regression-Based Inequality Decomposition proposed by Fields (2003). Such index is a common Inequality index in the specific literature which satisfies the scale-independence property and the population principle (Goerlich, 1998) but it does not satisfy the Pigou-Dalton transfers principle as long as the observations are greater than *e* times the geometric mean of the distribution in question, what only affects the very high values of the distribution with no significant effect in our analysis (Foster and Ok, 1999; Cowell, 2011)

Figure 2. International EF-Inequality according to variance of logarithms



Note: own elaboration

3- METHODOLOGY: THE REGRESSION BASED INEQUALITY DECOMPOSITION

In contrast to the traditional analytical method of decomposing inequality, which is based purely on mathematical properties (see Shorrocks 1982, 1983), RBID allows not only for inequality accounting but also causal analysis. Actually, the main advantage of such relatively new methodology (Fields, 2003) is that it does not require the variable of interest to be broken down into its components (what in EF framework would be decomposing inequality according to the contributions of carbon, cropland, grazing, fishing, forest and built-up footprints)[6]. On the contrary, RBID permits accounting for the inequality contribution of any significant explanatory factor. Hence, all that is needed is an auxiliary regression such as those pollution generating functions estimated within the framework of environmental economics, which are an expanded Environmental Kuznets curve or STRIPAT model:

$$EF = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_k X_k + \varepsilon_i \tag{1}$$

There is a vast empirical literature in environmental economics estimating such functions, i.e. an environmental Kuznets Curve (Caviglia-Harris et al., 2009; Dinda, 2004; Grossman and Krueger, 1991; Torras & Boyce, 1998) or stochastic estimations of IPAT identity (Dietz et al., 2007; Rosa et al., 2004; York et al., 2003). But, to our best knowledge, such results have never been used to analyze international differences among countries.

By construction, in expression (1) EF is presented as the sum of its *k* explanatory variables plus a typical error term and constant term, so it can be expressed as

$$EF = \sum_{k}^{K+2} \beta_k X_k \tag{2}$$

The RBID is based on considering the product of estimated coefficients and its variable as a composite variable, where the coefficients (β) play the role of weighting the importance of the component *k* in contributing to whole EF. As a result, a consistent

[6] White (2007) and Teixido-Figueras and Duro (2012) decompose the International Ecological Footprint Inequality according to the contribution of EF components. The main results indicate that the most important contribution to EF inequality became the carbon footprint because of its rising share in total EF rather than because of its inequality, which actually decreased. In contrast, Grazing and Fishing footprints (related to the diets of industrialized countries) exhibited relatively high levels of inequality despite contributing modestly to total EF inequality because of its low share to total EF. Finally Cropland footprint contribution to EF inequality reduced significantly as a result of both having historically low inequality (basic subsistence highly depends on cropland consumption) and having decreased its EF share in the course of the period.

identity is obtained in line with those required by traditional decomposition methods, so that the rule of natural decomposition of the variance can be performed in an analogous way and benefit from its persuasive axioms[7]. Under this decomposition rule, the contribution of each component corresponds to the cov(X_k, EF) and its relative contribution is defined as cov(X_k, EF)/var(EF) (see Shorrocks 1982, 1983).

Although there are other methods to decompose inequality using regression-based techniques, we use the Fields method (Fields 2003) because of its simplicity and analogy to Natural Source Decomposition described above[8]. In this RBID approach the model is restricted to a semi-log linear function[9]:

$$\ln EF = \sum_{k}^{K+2} \beta_k X_k \tag{3}$$

Once the semi-log model is estimated, variances on both sides of the equation must be taken:

$$\operatorname{var}(\ln EF) = \operatorname{var}\left(\sum_{k}^{K+2} \beta_k X_k \right) \tag{4}$$

Notice that the right hand side is already an inequality measure, the variance of logarithms. Rearranging the expression (4), we will obtain

[7] According to Shorrocks (1982) the natural decomposition of the variance is the only non-ambiguous decomposition of inequality by sources independently of the inequality measure used. The main reason is that correlation among components is allocated in an explicit and rational way without violating the basic axioms of inequality measurement (1- the inequality index and the sources are continuous and symmetric. 2- The contributions do not depend on the aggregation level. 3- The contributions of the factors add up to the global inequality. 4- The contribution of source *k* is zero if factor *k* is evenly distributed. 5- With only two factors, where one of them is a permutation of the other, the contributions must be equal.)

[8] There are several empirical applications to income comparing different methods. An appealing one is (Gunatilaka & Chotikapanich, 2009)

[9] The semi-log model $Ln(EFpc) = \beta_0 + \beta_1 F_1 + \beta_2 F_2 + ... + \beta_k F_k + \varepsilon_i$ is equivalent to

$EFpc = \exp(\beta_0 + \beta_1 F_1 + \beta_2 F_2 + ... + \beta_k F_k + \varepsilon_i) = \exp(\beta_0) \cdot \prod_{k=1}^{k} \exp(\beta_k F_k) \cdot \exp(\varepsilon_i)$. Then, the contribution β_0 is null since it is a constant to each observation.

$$\mathrm{var}(\ln EF) = \sum_{k}^{K+2} \mathrm{cov}(\beta_k X_k, \ln EF) = \sum_{k}^{K+2} \mathrm{cov}(\beta_k X_k, \ln EF) \tag{5}$$

which is an analogue of the expression of the natural decomposition rule of the variance (Shorrocks 1982). Therefore, according to this method, the contribution of EF's explanatory factors, x_k, to total EF inequality is defined by

$$s_k(\ln EF) = \frac{\mathrm{cov}\left[\beta_k x_k, \ln EF\right]}{\mathrm{var}(\ln EF)} \tag{6}$$

Notice that $\sum_{k=1}^{K+2} s_k(\ln EF) = 100\%$ so that s_k answers the question of how much EF inequality is accounted for by the factor k. If we remove the residual term, then what we will get is R^2 of the regression $\sum_{k=1}^{K+1} s_k(\ln EF) = R^2\,(\ln EF)$

Since the coefficients of the regression play a weighting role, it may be interesting to know whether the different evolutions of s_k are caused because of change in the dispersion of factor k, or by a change in its importance in the function measured by β. Expression (7) provides a decomposition of just such an evolution of the s_k contribution

$$s_{kt} - s_{kt-1} = \frac{\mathrm{cov}(Z_t^k, \ln E_t)}{\mathrm{var}(\ln E_t)} - \frac{\mathrm{cov}(Z_{t-1}^k, \ln E_{t-1})}{\mathrm{var}(\ln E_{t-1})} =$$

$$\left[\frac{\mathrm{cov}(\hat{Z}_{t-1}^k, \ln E_t)}{\mathrm{var}(\ln E_t)} - \frac{\mathrm{cov}(Z_{t-1}^k, \ln E_{t-1})}{\mathrm{var}(\ln E_{t-1})}\right] + \left[\frac{\mathrm{cov}(Z_t^k, \ln E_t)}{\mathrm{var}(\ln E_t)} - \frac{\mathrm{cov}(\hat{Z}_{t-1}^k, \ln E_t)}{\mathrm{var}(\ln E_t)}\right] \tag{7}$$

Where $Z_t^k = \beta_t^k x_t^k$ and $\hat{Z}_{t-1}^k = \beta_{t-1}^k x_t^k$. The first term is the dispersion effect since the coefficients are not allowed to vary (and so only the dispersion changes between *t-1* and *t*) and the second term is the coefficient effect since the dispersion of vector x is not allowed to vary (and so only the coefficient changes between both periods).

Additionally, we may be interested in knowing to what extent the *k* factor contributed to the change in the EF inequality level between two periods. This inequality change contribution is expressed as:

$$\delta_k \equiv \frac{s_{kt} I(.)_t - s_{kt-1} I(.)_{t-1}}{I(.)_t - I(.)_{t-1}} \tag{8}$$

Notice that expression (8) is not restricted to the use of any particular inequality index. However, unlike the previous decompositions described, the results in (8) do depend on the inequality measure chosen.

4- DECOMPOSITION RESULTS FOR INTERNATIONAL ECOLOGICAL FOOTPRINT INEQUALITY

In this section, the method developed in the previous section (Fields, 2003) is performed in order to quantify the contribution of various factors in accounting for the amount of international EF inequality at a point in time (equation 6), their change over time, its functional decomposition (equation 7) and, finally, the role they played in the increase of the EF inequality observed (equation 8). Before all this, however, it is necessary to estimate the auxiliary regression.

The data used comes from the World Bank and from the Ecological Footprint Network and covers the period from 1993 to 2007, biannually. Each year uses at least 87% of the world EF, at least 94% of the world population and, at least 96% of world GDP. The explanatory variables used as factors are those typically regressed in STRIPAT models and extended EKC curves and are listed in table 2 (see York et al. 2003). Notice that table 2 provides, apart from the typical descriptive statistics, the ratio between the standard deviation and the mean of the variables (Coefficient of Variation), which may allow comparisons among internal inequalities of each variable.

Table 2. Descriptive statistics

Variable (1993)	Obs	Mean	Std. Dev.	CV	Min	Max
EF pc -global hectares per capita	132	2.782	1.933	0.695	0.497	11.115
per capita GDP (constant 2000 US$)	132	4963.830	7985.772	1.609	79.581	35963.800
Industrial GDP share (%)	132	30.377	10.196	0.336	8.825	63.996
Urban population share (%)	132	49.891	23.014	0.461	6.840	100.000
Nondependent population share (aged 15 to 65)	132	58.940	6.717	0.114	45.528	72.130
Average daily min temperature	132	12.132	8.098	0.667	-10.100	23.300
Variable (2007)	**Obs**	**Mean**	**Std. Dev.**	**CV**	**Min**	**Max**
EF pc -global hectares per capita	132	3.018	2.070	0.686	0.62	10.68
per capita GDP (constant 2000 US$)	132	7313.431	11217.280	1.534	96.25	56388.99
Industrial GDP share (%)	132	32.881	12.610	0.384	13.27	76.42
Urban population share (%)	132	55.797	21.664	0.388	12.56	100.00
Non-dependent population share (aged 15 to 65)	132	63.024	6.597	0.105	48.81	81.44
Average daily min temperature	132	11.981	8.006	0.668	-10.10	23.30

Note: further descriptive data is available upon request. CV refers to the Coefficient of Variation, an inequality index consisting in dividing standard deviation into mean

4.1 Auxiliary regression results

The first step in the decomposition analysis consists in running equation 3. Since the model is a semi-log model, the dependent variable is per capita EF in log scale and it consists of a linear function of GDP per capita (and its square and cubic terms), industrial GDP share, urban population share, non-dependent population share and climate control variable. The results obtained by an OLS are shown in table 3. The first thing to note is that high values are registered in R^2. Considering that high values in the adjusted R^2 in the cross-sections are accompanied by high significance in the variables, collinearity is not a problem in the model estimated (Pindyck and Rubinfeld, 1998). We calculated quadratic partial correlations between exogenous variables and dependent variables and low values were obtained indicating, once more, that collinearity is not a problem in our estimation[10].

Since it is a semi-log model, we must interpret the significant coefficients such as semi-elasticities, i.e. an increase (decrease) of one unit in an explanatory variable yields a β% increase (decrease) in the dependent variable. Hence, an increase in one dollar of per capita GDP yields an increase of EF per capita of 0.01%, and so on (in low income countries).

The coefficient signs are consistent with those results obtained by other authors: firstly, the affluence factor, here approximated by GDP per capita (which should not be confused with welfare[11] but with economic activity), indicates the existence of a non-monotonic relationship given the negative sign in the quadratic term of GDP, pointing to an Environmental Kuznets Curve (EKC) relationship. However, the significant positive cubic term of GDP per capita rejects such a hypothesis. This is an N-shape pattern[12] and, implicitly, the rejection of the EKC hypothesis is obtained in all of the studies of sample years. Therefore, all other things being equal, GDP per capita raises EF per capita. The more affluent the country, the more resources it demands and so the lower the sustainability. In this regard, the strictly economic degrowth theories may solve the distributional problems with future generations as environmental pressure

[10] Other models have been estimated with different regressors, including models where cubic GDP per capita is removed and the results obtained are virtually equivalent. Actually, as can be expected, the higher correlation belongs to this variable. It must be taken into account, however, that the non-collinearity assumption is about linear relationships among regressors, and despite its high correlation with GDP per capita, the cubic GDP per capita is a non-linear relationship. Hence, it does not violate the basic assumption (Gujarati & Porter, 2009).

[11] GDP per capita is conventionally used as a measure of society's welfare. However, it only measures the total *monetary* value of goods and services produced within a country's borders in a given year. It does not necessarily correlate with access to healthcare, wealth distribution and literacy. Indeed, those defensive expenditures that aim at avoiding or correcting social or ecological impacts caused by GDP growth, are also positively added into GDP accounts.

[12] Other studies finding this N-pattern relationship between GDP per capita and environmental pressure are Friedl and Getzner (2003), Sengupta (1996), Taskin and Zaim (2000)

would, however, slow down at the cost of aggravating resource distribution conflict between people of the same generation since, despite huge inequalities, growth can make everybody at least a bit better off.

The economic structure, approximated here by the industrial share of GDP, appears with a negative sign that is not always significant. Thus, as long as the environmental impact is measured with EF, a greater share of industry involves lower EF per capita in comparison to non-industrial sectors (services and agriculture). Such a result is quite different from results obtained in the literature when the ecological impact is measured with some more production-based indicators. Nonetheless, it is consistent with estimations done with EF (York et al. 2003). EF is a consumption-based indicator, therefore having a more industrial-based GDP does not necessarily imply consuming more resources (countries may be exporting their products and global hectares exported are subtracted from a country's EF). In fact, for several years, the coefficient is not statistically different from zero.

The more population that lives in urban areas, the more EF per capita is exhibited. The rationale stems from the fact that the migration of rural workers to urban areas in search of better jobs yields a sprawl of growing cities with large suburbs and thus more roads, wires and infrastructures per capita are required. Additionally, in urban zones, the need to commute every day by private vehicle becomes more pressing. Therefore, the EF per capita tends to be higher as urban population is also higher. In effect, although the impact of urban development is often perceived as local or regional, cities have become entropic black holes drawing in energy and matter from all over the ecosphere (Alberti, 1999; Rees and Wackernagel, 1996). Nonetheless, the coefficient is quite low (a 1% rise yields a 0.5% rise in EF per capita) and registers a slight shrinkage over the period analyzed.

Still, in demographic terms, the share of Non-Dependent Population (this is the population aged between 15 and 65, and so of working age) raises the demand of resources per capita by around 2% for each additional percentage point in such a variable. This is caused because the ages of between 15 and 65 are the most productive and also the most consumerist ones and so the EF per capita of a country with high share of this adult population will tend, naturally, to be higher. In other words, children may consume substantially less natural resources than adults but as they grow they will consume further cars, flights, tobacco, clothes, furniture, etc., so increasing their EF, but as they reach the later stages of life they may moderate some of this consumption (Zaguenhi, 2011) [13]. In this regard, we may expect that, as populations of the low fertility nations of the world grow older, resource consumption patterns may shift radically (Dietz and Rosa, 1994). *Ceteris paribus*, this is what the regression coefficient is indeed capturing.

Lastly, climate plays a role in influencing patterns of ecological impact. Here, we used a climatic normal[14] instead of a dummy variable to take advantage of its greater variability[15]. Concretely, the daily minimum average temperature is used as a control for such a role. The negative sign obtained thus indicates that the colder (the hotter) the weather, the higher (the lower) the environmental impact. It might be caused by higher energy demands.

[13] Zaguenhi (2011) results point out that per-capita CO_2 emissions in the US increase with age until the individual is in his or her 60s, and then emissions tend to decrease.
[14] Climatologists define a climatic normal as the arithmetic average of a climate element (such as temperature) over a prescribed 30-year interval in order to filter out many of the short-term fluctuations and other anomalies that are not truly representational of the real climate. The last climatic normal available is for the period 1971-2000
[15] Many studies used dummy variables coded into three categories based on the latitude of a country: arctic, tropical, temperate. See York et al. 2003.

Table 3. OLS coefficients predicting the National Ecological Footprint per capita.

Variable	1993	1995	1997	1999	2001	2003	2005	2007
Affluence								
per capita GDP	.00010702***	.00013775***	.00011086***	.00012868***	.00013551***	.00014331***	.00011793***	.00012602***
pc GDP 2	-5.647e-09**	-6.272e-09**	-4.822e-09**	-5.300e-09***	-5.502e-09***	-5.911e-09***	-4.244e-09***	-4.387e-09***
pc GDP3	9.325e-14*	9.135e-14*	6.840e-14*	6.930e-14**	7.051e-14***	7.646e-14***	4.887e-14***	4.657e-14***
Sectorial Composition								
Indust. GDP share (%)	-.00567775*	-0.0053	-.00749226**	-.00715216**	-.00599264**	-.00534894**	-0.00342	-0.00111
Population Structure								
Urban population sh	.0051429**	.0042*	.00510013**	.00468959**	.00413376**	.00439423**	.00514963***	.00410505**
Non-dependent pop	.02001067**	.01562846**	.02191975***	.01635892**	.01656801**	.01459613**	.01706415***	.0180932***
Climate								
Avg. min temperature	-.0198924***	-.01331806***	-.0131226***	-.00912717*	-.01044084**	-.00897584**	-.01148746***	-.01165549***
Constant	4.1722791***	4.2730793***	3.9271276***	4.148702***	4.1207606***	4.163932***	3.9771418***	3.8762283***
Countries	132	136	137	137	139	141	137	132
Squared R	0.71	0.71	0.73	0.71	0.73	0.75	0.77	0.77
Adjusted Sq R	0.69	0.70	0.71	0.70	0.72	0.74	0.76	0.75
log-likelihood	-42.6265	-48.1674	-45.6984	-49.3509	-48.4103	-44.3009	-38.6825	-38.5654

*, **, *** significant at the 10%,5% and 1% level, respectively

4.2 Regression Based Contributions of Factors

The regression results are used to calculate each factor's weight which, jointly with the variable vector dispersion (its inequality), will yield the contributions to overall EF per capita inequality observed[16]. Table 4 presents, on the left, the relative factor contributions to inequality (expression 12) for each year sampled from 1993 to 2007 and on its right, the contribution change registered throughout the whole period analyzed (1993-2007) is decomposed in order to quantify to what extent that change is due to changes in a factor's dispersion or to its coefficients. Lastly, table 5 quantifies the contribution of each factor to the rise observed in international EF inequality as measured by Log-Variance.

As can be seen, despite the bulk of the variables being statistically significant determinants of EF per capita, not all of them share the same importance in accounting for cross-country inequality in EF per capita. These differences in relative importance could not have been seen from standard regression output alone (Fields, 2003).

[16] Non-linear effect of GDP per capita (say quadratic and cubic) is grouped into the affluence factor, following Fields' (2003) methodology.

Table 4. Decomposition of Inequality, Contribution Level and Decomposition of Contribution Change by the dispersion-coefficient effect

	Contribution level								Dispersion and Coefficient effect in contribution changes 1993 - 2007				
Factors	**1993**	**1995**	**1997**	**1999**	**2001**	**2003**	**2005**	**2007**	**Change 1993 - 2007**	**Disp. Effect**	**(%)**	**Coeff. effect**	**(%)**
Affluence													
GDP per capita	28.26	42.89	36.62	44.11	47.2	50.36	46.8	48.93	+20.40%	13.3%	(65%)	7.20%	(35%)
Sectorial Composition													
Indust. GDP share (%)	-1.75	-1.46	-1.15	-0.61	-0.55	-0.38	-0.02	-0.04	+1.70%	1.5%	(90%)	0.20%	(10%)
Population Structure													
Urban population sh	13.3	10.39	12.47	11.23	9.58	10.13	11.77	8.86	-4.40%	-2.2%	(50%)	-2.20%	(50%)
Non-dependent pop	15.9	11.32	16.13	11.16	11.17	9.74	11.29	11.83	-4.00%	-2.8%	(69%)	-1.20%	(31%)
Climate	15.29	8.35	8.49	5.31	5.99	5.06	7.19	7.07	-8.20%	-3.2%	(39%)	-5.00%	(61%)
Residual	28.99	28.51	27.43	28.8	26.62	25.09	22.97	23.35	-3.90%	-3.9%	(100%)	0.00%	(0%)
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**					

Table 5. Contribution of that factor to the change in inequality measured by:

Factors	**Log-Variance 1993-2007**	**Generalized Entropy (2) 1993-2007**
Affluence	172.39	730.52
Sectorial Composition		
Indust. GDP share (%)	10.14	56.18
Population Structure		
Urban population sh	-17.66	-137.53
Nondependent pop	-12.52	-122.58
Climate	-42.02	-263.97
Residual	-10.33	-162.62
Total	**100.00**	**100.00**
Total Inequality change	**17%**	**3%**

The affluence factor accounted for the largest share of total EF inequality throughout the whole period. In 1993 it already accounted for the 28.26% and registered a sharp increase throughout the period until accounting for 50% of the EF inequality. Consequently, it can be stated that the most important factor in determining the international EF inequality level was the affluence factor, especially in the last years of the sample where it accounted for half of the total EF inequality. Furthermore, taking into account that in the period analyzed, as figure 2 showed, international EF inequality increased (according to log-variance), the fact that the contribution of affluence registered such an increase inevitably means that this inequality factor increased faster than EF inequality (see equation 6). As table 5 (right) shows, such an increase in affluence contribution was not entirely driven by an increase in its own dispersion: a sizeable 35% of that increase between 1993 and 2007 was driven because of changes in the regression coefficient (being the remaining 65% due to the dispersion effect). Finally, as table 5 presents, the rise of EF inequality observed in the period was mainly driven by the contribution of the affluence factor. What we see then, is that the affluence factor not only is the main contributor to EF inequality but also the main driver (if not the only one) that spurred international inequality in terms of natural resource consumption (176% of the increase in log variance). Hence, in terms of *intra*generational inequality, it is proved that what determines the direction of resource flows in the world's system is essentially the purchasing power of countries.

Considering the remarkably high importance of the affluence factor in determining and in raising EF inequality, this finding expands the typical regression result qualitatively, hence, all other things being equal, as countries get richer, they tend to require a larger EF per capita (regression result) but in doing so, international inequality in the EF per capita is also encouraged (RBID result). Therefore, decoupling policies[17] will undoubtedly improve sustainability as many papers point out; however, the results shown indicate that neglecting GDP per capita convergence will still lead to a high EF inequality (a sustainable but inequitable world system) and probably, it will hinder the

[17] Decoupling policies are those policies that are aimed at reducing the relationship between certain variables, which in this case is GDP growth, and its associated environmental pressure, in this case EF. This relationship is quantified here by the auxiliary regression coefficient β.

achievement of sustainability ; for instance, the more unequal the per capita income is, the more difficult it will be to reach multilateral environmental agreements, since poor countries will have more pressing concerns to prioritize, and as a result, they will be more reluctant to engage in costly commitments. Rich countries, which could compensate them by transfers, do not have enough guarantees that those transfers will be used to achieve environmentally agreement objectives (Neumayer 2011). Indeed, there is some evidence from field experiments demonstrating that the more inequality that exists among individuals, the greater the concern about the fairness of the outcome rather than the achievement of the objective itself, which here is sustainability (Tavoni et al. 2011). Therefore, international policies should be aimed at two objectives: first, decoupling GDP and the demand for natural resources and second, fostering economic convergence to benefit its plausible positive synergies (for instance, those compensating transfers from rich to poor countries). In the light of the results, such policies will clearly be the most effective ones in achieving an equitable sustainable world.

The sectorial composition factor, approximated here by the industrial share of GDP, appears with a negative contribution to EF inequality (table 4 right). This means that this factor not only does not contribute to inequality but lowers EF inequality. The reason for this particular behavior is twofold: firstly, the factor registers relatively low inequality among countries (compared to EF per capita inequality; see table 2), and secondly, its coefficient (weight) is also relatively low in explaining EF per capita (a 1% increase in industrial share lowers the EF per capita by 0.5-0.7% as long as the statistical significance holds). Nonetheless, since the still low inequality in industrial share increased modestly during the period, 90% of the change in that factor's contribution to EF inequality was due to a dispersion effect (table 4 right). Given the increasing EF inequality scenario, the modest change in the unequalizing direction of the factor makes the contribution to EF inequality significant (10% of log-variance increase in table 5). In any case, inasmuch as the coefficient is not statistically different from zero over several years, we may conclude that industrial share is not an important factor either in its causality or in its international inequality.

Urban population share, related to the additional resources per capita needed through living in urban areas, exhibits a sizeable although decreasing contribution to international EF inequality. At first, urban share was responsible for 13.3% of international differences but at the end of the period it decreased until representing just 8.86% of the differences (table 4). This is caused on the hand by a decrease in the internal inequality of the factor (table 2), and on the other hand to the slight decline in its regression coefficient (table 3). Such a change in urban factor contribution was thus driven equally by both dispersion and coefficient effect (50% and 50%), since both the factor's inequality and coefficient reduced equally throughout the period. The changes registered explain the negative contribution of the factor to rising EF inequality (table 5). In this regard, it could be stated that the urban factor avoids greater EF inequality. In this case however, such a fact is not necessarily good: what we are observing in this particular factor is that humanity is converging on urban environments (and so its inequality is low and declining) but, since its coefficient is still positive in explaining EF per capita, such an urban convergence may involve a greater impact. According to UN Habitat (2012) urban areas around the world are becoming the dominant form of habitat for humankind[18]. Therefore, in terms of sustainability, it becomes critical to continue lowering that coefficient. In this regard, the low coefficient with its slight reduction in our results may be suggesting that some potential advantages of urban

[18] According this report, only one century ago, two out of ten people in the world were living in urban areas, in 1990 less than 40%, and since 2010, more than half the world population is settled in a city (UN Habitat, 2012).

settlements may be playing a faint role in decoupling urban population from EF per capita; for instance, urbanization involves lower demand for occupied land because of high population density and it also provides great potential for economies of scale (in recycling, providing piped treated water, waste collection and other public amenities) and for reducing energy consumption through walking, cycling or public transit (Rees and Wackernagel, 1996). Hence, given this urban convergence trend, such potentialities must be fostered in order to completely decouple cities from their environmental impact[19] in order to ensure sustainability. Otherwise, the other option is stopping the massive migration to cities.

Contrastingly, the second demographic factor captured, the non-dependent population (a country's age structure) exhibits a relatively high coefficient (table 3) and a relatively low international inequality (compare its CV with EF per capita CV in table 2). Consequently, its also sizeable contribution to EF inequality is mainly due to its importance in causing EF per capita rather than in exhibiting internal inequality. Hence the non-dependent population factor's contribution is a factor mainly driven by its high coefficient, which is its weight in explaining EF per capita. However, as shown in table 4, this contribution reduced from 15.9% to 11.8%, and it was due mainly to the dispersion effect (69%) rather than a coefficient effect (31%). Therefore, on average, it was mainly the fact that countries became more equal in terms of their demographic pyramid structure that caused the reduction in the factor's contribution. This equalizing movement led to the age structure contributing negatively to the rise in EF inequality (table 5). As a result, focusing on the non-dependent population share, the only possible policy recommendations which would ensure both a fairer distribution of natural resources and higher sustainability rates, would be those that make the factor's

[19] There is vast literature focused on the study of how different urban patterns can affect ecological systems. See Alberti 1999 for a review or Muñiz and Galindo (2005) for a case study.

coefficient shrink so that the working-age population was decoupled from its higher ecological impact, which may involve deep political implications since the social reproduction of capitalism is highly dependent on its consumerism and productive capacity.

Climate differences among countries contributed significantly to international EF inequality. Since the climate factor does not change throughout the period (it is a climatic normal), its reduction was caused by the statistical effect produced by the increase of log variance in EF per capita and changes registered in the regression. Nonetheless, it is worth highlighting the fact that the climate factor is the only non-anthropogenic factor of the empirical model considered, so that its evolution reinforces the idea that international inequality of resource consumption is mainly and increasingly a matter of human societies. Otherwise, inequality in natural resource use would not be unfair.

Finally, the residual contribution corresponds to that part of EF per capita variance that is not explained by regressors. From a statistical point of view, the reduction of the residual's contribution indicates a better fit of the model used (as R^2 point out in table 4). However, focusing on these kinds of environmental economics models, which stem from IPAT identities, the T of Technology is usually included in the residual term rather than estimated separately as a measure of resource efficiency (see York et al. 2003, p. 354). Therefore, in a very cautious way, and insofar as we assume that the residual is mainly capturing the technological capacities of countries, it may involve the technological differences among countries contributing a significant 28% to international EF inequality in the first years, reducing to a still significant 23.35% in 2007.

5- CONCLUSIONS AND POLICY IMPLICATIONS

This paper wishes to contribute to the literature which deals with ecological inequalities. In particular, we estimate the influence of anthropogenic driving forces of environmental impact on the International Inequality of natural resources. In doing so, we extend those empirical analyses that, by regression techniques, estimate the elasticities of the drivers' ecological impact. As a result, the analysis performed shows and discusses not only the intergenerational equity (future generation's rights) but also the often neglected *intra*generational equity. We use Ecological Footprint data to measure a country's demand for natural resources.

From a technical point of view we have applied a relatively new methodology, the Regression Based Inequality Decomposition (Fields 2003), in order to obtain the building blocks of international EF inequality. The empirical literature on this issue was limited to the use of additive sources of the environmental indicator as contributors to its inequality. In the case of Ecological Footprint inequality, for instance, the contributors to total EF inequality were limited to the contributions of its additive components (carbon, cropland, grazing, forest, fishing and built-up footprints) by applying traditional inequality decomposition tools. However, the regression based approach allows decomposing the inequality into explanatory variables typical of environmental threats such as per capita GDP, sectorial composition, population structure, climate and technology. As a result, the analysis performed is critical to understanding the main determinants of international EF inequality per capita.

The main results demonstrate that economic growth not only increased ecological impact per capita but also its ecological inequality within countries. Such a finding expands the typical growth-environmental damage trade-off: as countries became more affluent, it led not only to a more unsustainable scale but also to a less fair allocation of natural resources, which may yield a circle of unsustainability and inequity, given the potential interactions between them. Indeed, economic convergence may yield a more equitable distribution of natural resources within and between generations. Hence, decoupling policies should be combined with economic convergence policies, such as relative transfers from rich to poor.

On the other hand, demographic variables also play a critical role in EF inequality. Firstly, we observed that world population is migrating from rural to urban environments and, according to international studies, it is not expected to end in the coming decades. Hence, it becomes of paramount importance to keep lowering the still positive link between cities and greater EF per capita by redesigning the existing cities in a rationally ecological way, i.e. taking advantage of cities' potentialities given its economies of scale and its high population densities: co-generation, public mobility, material recycling and re-use, etc. Such policies may prevent future generations from ecological overshoot and at the same time will yield a more just distribution of natural resources within present generations. In a more ambitious way, policies oriented to preserving rural population share will also work with the same objective. Secondly, the demographic pyramid shape also plays a significant role in explaining EF differences among countries, mainly because of the greater consumption of working age populations. Hence, it may become critical to foster policies to detach that population group from its ecological impact, which may also involve both more ecological equality among countries and greater sustainability.

In contrast, the structural composition of economies does not contribute to EF inequality not only because of a low number of differences among countries but also because of its weight (regression coefficient) in explaining EF per capita, which actually is not always significantly different from zero. Finally, we observed that climate characteristics of countries do not play an important role over the last years, so that EF inequality is mainly a matter of social relationships among countries.

On balance, this paper wants to encourage global governance to pursue the satisfaction of future and present generations' claims simultaneously and with the same vehemence; in doing so, some positive synergies may help achieve both equity and sustainability. Following this line, the main policy recommendations highlighted in the paper are: first, decouple economic growth from its environmental impact without neglecting the economic convergence among countries; second, given the urban convergence of humankind, policies oriented at reducing the ecological impact of urban environments are critical to ensure sustainability, third, the ecological impact of the working-age population should also be reduced to make the use of natural resources more sustainable and equitable. Therefore, at the end of the day, policies aimed at decoupling the link between the anthropogenic driver and the ecological impact (the coefficient) will have twofold consequences: it will definitely improve future generations' chances and consequently environmental sustainability and, secondly, it will reduce *intra*generational inequality in resource consumption.

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