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Measuring progress towards a 'Green Energy Economy': Who is really winning the race?

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Abstract

This paper provides the first regional econometric decomposition of CO_2 emissions from fuel combustion in eight regions of the world. Using the best publically-available time series data (1971–2011), the analysis examines the key determinants and relationships of the 'Green Energy Economy' (GEE) in Africa, Asia, Latin America and the Caribbean, the Middle East, Non-OECD Europe and countries from the Former Soviet Union, Oceania, OECD Europe, and OECD North America. The results show that emissions continued to grow across all regions, at rates ranging from 0.1% y^{-1} to 7% y^{-1} for the period under analysis. Despite progress in energy intensity (e.g. Asia) and carbon dioxide intensity of the energy supply (e.g. OECD Europe), GDP per capita (or *'affluence'*) was found to be a key driver of accelerating CO_2 emissions in most regions. In certain cases, a sharp but short term decrease in CO_2 emissions was identified; however, these reductions did not appear to correlate with income levels or other explanatory variables, but rather to a historical exogenous shock. Findings show that the opportunity offered by the 2008–2009 global financial crisis to move towards a GEE, at least in terms of reduced CO_2 emissions, was missed in nearly all regions. From a policy perspective, the analysis strongly suggests that regional policy portfolios aimed at market uptake of green energy technologies are still insufficient and/or ineffective and that great ambition level is needed.

Keywords: CO_2 emissions; gross domestic product; energy intensity of economy; carbon intensity of energy supply; econometric analysis; decomposition analysis

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1. Introduction

The concepts of the 'Low-Carbon Economy', the 'New Green Economy' and 'Green Economic Growth' received increasing policy and media attention following the 2008–2009 global financial crisis (Barbier 2010; Allen and Clouth 2012). The crisis was particularly significant as it highlighted that the traditional production-and-consumption economic model had led to significant loss of natural capital, disturbances in the climatic system, and had been the driver for social inequalities. Moreover, it proved that the system was economically unreliable (Jackson 2011). The crisis triggered numerous policy pledges to reform economic models towards a 'green growth' path that was not only environmentally and socially acceptable, but also was able to sustain the economic system.

At this time, it was argued that the financial crisis provided an important opportunity to decrease fossil fuel dependency and capitalise on absolute reductions in CO_2 emissions resulting from the economic downturn (IEA 2009; Peters et al. 2012). In turn, economic recovery packages were implemented in countries across the world, which aimed to stimulate green growth and support low-carbon economies, among other policy objectives (e.g. employment). These stimulus packages were quickly portrayed as the dawn of the Green Energy Economy (GEE), in which clean energy would play a vital role. Green energy was the target of recovery packages in many countries, and China and South Korea soon became the world leaders in green spending. For instance, by 2010, South Korea had allocated nearly 95% of its US$38 billion fiscal stimulus program to green investments (Barbier 2010). Of this, more than 30% was dedicated to energy-efficient buildings, renewable energy and low-carbon vehicles (UNEP and GEI 2009). China allocated more than 30% of its US$ 647 billion stimulus package to green measures (Barbier 2010). Of this, 13% targeted energy-efficiency measures related to buildings and low-carbon vehicles (UNEP and GEI 2009). In the United States, financial support for low-carbon technologies accounted for more than 70% of the US$ 92 billion devoted to green spending through the 'American Recovery and Reinvestment Act' (Council of Economic Advisers 2010). Despite these huge sums, the latest research (e.g. Peters et al. 2012; Jotzo et al. 2012) shows that the *global* economy does not appear to have seized the GEE opportunity—at least when measured in climate mitigation terms. In fact, CO_2 emissions have risen faster in recent years than in previous decades.

Although reports of global emission trends are consistent across the scientific literature, there is little data available regarding trends in *regional* CO_2 emissions and their drivers, in particular progress towards a GEE from a climate mitigation point of view. We know there is a high level of heterogeneity in economic growth, climate and energy policy portfolios, energy supply mix, technology development, and the resulting CO_2 emissions across regions in the world. However, to date most (econometric) decompositions have either focused on specific countries (e.g. the United States, China or Brazil) or particular regions (e.g. Europe, OECD, non-OECD) (e.g. Casler and Rose 1998; Jotzo et al. 2012; Luukkanen and Kaivo-Oja 2002; Wang, Chen, and Zou 2005). We still know very little about key GEE indicators (such as energy or CO_2 intensity), their relation to economic growth and resulting CO_2 emissions, in for instance, Latin America, the Middle East or Africa. This is despite the fact that the causes and/ or impacts of climate change are usually presented or discussed in regional (or sectoral) terms (e.g. as reflected in the Intergovernmental Panel on Climate Change Assessment Reports). What is also striking is the lack of *regional* studies that analyse and test economic-environmental phenomena against theories and observations about the relative contribution of macroeconomic variables to CO_2 emission trends. In addition there is a lack of *regional* quantitative knowledge regarding the effectiveness of the numerous economic recovery packages that were implemented following the financial crisis aimed at stimulating green economic growth through the deployment of low-carbon technologies. Data constraints may explain this knowledge gap, which this paper attempts to fill.

We found two notable exceptions to these observations. Raupach et al. (2007) analysed both global and regional drivers of CO_2 emissions. However, their analysis, which addressed four countries and five regions for the period 1980–2005, was limited compared to the research at hand (details below).

The second study by Mundaca et al. (2013) provides a decomposition for eight regions of the world (1971–2010), but lacks a statistical analysis of key determinants and estimated trends. Although these studies provide interesting insights, other questions remain to be answered: What have been the key *regional* drivers of increasing CO_2 emissions in the past four decades? To what extent can theory and observation explain the historical and current economic-environmental phenomena seen across regions of the world? How important is 'affluence' in explaining emission patterns? Does population growth still play an important role in emission trends in less industrialised regions? What can be said about energy intensity or the decarbonisation of the fuel mix across regions? How strong (or weak) was the 'carbon rebound effect' across regions after the global financial crisis? In terms of climate mitigation efforts, which regions have made progress towards a GEE since 'green' stimulus packages were introduced?

This paper is the first regional econometric decomposition of CO_2 emissions from fuel combustion. It covers eight regions of the world and is based on the best publically-available time series data (1971–2011). It provides a better understanding of *regional* economic-environmental phenomena based on contemporaneous theory and observations of macroeconomic variables. The quantitative analysis measures progress (or lack of it) towards a GEE. The methodology builds upon theoretical and empirical developments related to the 'IPAT equation' and the 'Kaya Identity' (see next section). It identifies the key GEE macro determinants for: (1) Africa, (2) Asia, (3) Latin America and the Caribbean (LATAM), (4) the Middle East, (5) Non-OECD Europe and countries from the Former Soviet Union (FSU), (6) Oceania, (7) OECD Europe, and (8) OECD North America. Overall, the paper offers a high-resolution regional econometric decomposition. It is structured as follows: Section 2 provides methodological details. Key findings are presented in Section 3 and we draw some conclusions in Section 4.

2. Methodology

The methodology was based on a top-down econometric decomposition aimed at finding significant statistical relationships between a dependent variable (CO_2 emissions from fuel combustion) and various independent variables (e.g. economic activity, population growth). The world is divided in eight regions. Key elements of the empirical analysis are described below.

2.1. Model specification

The 'I=PAT' equation[1] (Holdren and Ehrlich 1974) and the 'Kaya Identity' (Yamaji et al. 1991) are the theoretical frameworks used to initially define the model and pre-select regressors. The Kaya Identity builds upon the I=PAT equation; it is a macro decomposition of the energy, economic and demographic indicators used to quantitatively estimate CO_2 emissions as a product of four key aggregated drivers. Scientific research into the Kaya Identity has been critical in the development of future emission scenarios (see e.g. Nakicenovic and Swart 2000). In this study, and consistent with previous work (e.g. Raupach et al. 2007), the analysis began with the definition of the following 'global' structural model:

$$CO_2 = Pop\left(\frac{GDP_{ppp}}{Pop}\right)\left(\frac{TPES}{GDP_{ppp}}\right)\left(\frac{CO_2}{TPES}\right) = Pop\ g\ e\_int\ c\_int \quad (1)$$

where CO_2 represents global emissions from fuel combustion and industrial processes. Global CO_2 emissions are the product of four (potential) driving factors: *Pop* is the population, $\frac{GDPppp}{Pop}$ = g is the per-capita GDP_{ppp} (or 'affluence'), $\frac{TPES}{GDPppp}$ = e_int is the energy supply intensity of GDP_{ppp}, and $\frac{CO_2}{TPES}$ = c_int is the CO_2 intensity of the total primary energy supply (TPES) (see also Table 1).

[1] The I=PAT equation evaluates the contribution of population *P*, affluence *A* (GDP per capita or level of consumption per person), and technology level *T* (environmental impact per unit of GDP) on the overall environmental impact *I*.

Table 1: Variables, definitions and data source

Variable	Definition	Data source
CO_2 emissions	Emissions from fuel combustion (in million tonnes of CO_2[$MtCO_2$]), excluding emissions from marine and aviation bunkers, and following the IPCC Sectoral Approach	IEA(2013)
Population	All residents regardless of legal status or citizenship (in millions)	
Total Primary Energy Supply (TPES)	Production + imports − exports − international marine bunkers − international aviation bunkers ± stock changes (in million tonnes of oil equivalent [Mtoe])	
GDP_{ppp} per capita	Total annual output valued in billion 2005 US$ dollars, adjusted by purchasing power parities (ppp), and divided by midyear population (in 2005 US$)	
Energy intensity	TPES per GDP_{ppp}	
Carbon dioxide intensity	CO_2 emissions per TPES (in tonnes of CO_2 per Terajoule [tCO_2/Tj])	

Next the 'global' model was specified for eight regions: Africa, Asia, Latin America and the Caribbean (LATAM), the Middle East, Non-OECD Europe plus countries from the former Soviet Union (FSU), Oceania, OECD Europe, and OECD North America (see Table 2 for a definition of these regions). The disaggregated, 'regional' version of the original global model was then written as follows:

$$CO_2 = \sum_i CO_{2i} = \sum_i Pop_i \; g_i \; e\_int_i \; c\_int_i \tag{2}$$

where global emissions (CO_2) from fuel combustion and industrial processes are the sum of regional emissions (CO_{2i}). Regions and related (independent) variables are distinguished by the subscript *i*. Consequently, a regional multiple regression model was formulated as follows:

$$Y_{it} = \beta_{oi} + \beta_{1i}X_{1it} + \beta_{2i}\,X_{2it} + \beta_{3i}X_{3it} + \beta_{4i}\,X_{4it} + \mu_{it} \tag{3}$$

where Y_{it} = CO_2 emissions (in million tonnes) from fuel combustion (dependent variable) for region *i*, *t* = 1….. *T* years (=41); β_{0i} is a constant region-specific intercept; β_{1i} β_{2i} β_{3i} and β_{4i} are the regression coefficients to be estimated for X_{1it} (*Pop*), X_{2it} (*g*), X_{3it} *(e_int) and* X_{4it} (*c_int*) respectively; and μ_{it} is an error (or disturbance) term. This initial model was used for testing of individual regions (see next section). The analysis was based on time series data from the International Energy Agency (IEA) for the period 1971–2011(see IEA 2013).

Table 2: Definition of regions in the model

Region	Geographical coverage
Africa	Algeria, Angola, Benin, Botswana, Cameroon, Congo, Dem. Rep. of Congo, Côte d'Ivoire, Egypt, Eritrea, Ethiopia, Gabon, Ghana, Kenya, Libya, Morocco, Mozambique, Namibia, Nigeria, Senegal, South Africa, Sudan, United Rep. of Tanzania, Togo, Tunisia, Zambia, Zimbabwe, other Africa
Asia	Bangladesh, Brunei, Cambodia, Hong Kong (China), India, Indonesia, Israel, Japan, DPR of Korea, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, People's Rep. of China, Philippines, Singapore, South Korea, Sri Lanka, Taiwan, Thailand, Vietnam, other Asia
Latin America and the Caribbean	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Netherlands Antilles, Nicaragua, Panama, Paraguay, Peru, Trinidad and Tobago, Uruguay, Venezuela, other Americas
Middle East	Bahrain, Islamic Rep. of Iran, Iraq, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, Yemen
Non-OECD Europe and FSU	Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Georgia, Gibraltar, Kazakhstan, Kosovo, Kyrgyzstan, Latvia, Lithuania, FYR of Macedonia, Malta, Republic of Moldova, Montenegro, Romania, Russian Federation, Serbia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan, USSR (former), Yugoslavia (former)
Oceania	Australia, New Zealand
OECD Europe	Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom
OECD North America	Canada, Mexico, United States

2.2. Correlation and regression tests

Various correlation tests and regression statistics were used for assessing the relationships and contribution of variables to CO_2 emissions in each region. The initial hypothesis was that GDP_{ppp} per capita (*g*) was most closely correlated with CO_2 emissions and thus an important determinant. Three set of tests were carried out. First, bivariate correlation tests indicated correlation among the model's variables. These tests evaluated the relative degree of 'closeness' (or association) between each pair of variables. Secondly, partial correlations were calculated. This step was necessary as more than one variable could convey the same information (i.e. the problem of multicollinearity, where independent variables are themselves highly correlated) leading to unreliable estimates and high standard errors. A more important problem is that multicollinearity can make it difficult to draw any inferences about the relative contribution of a particular driver. Therefore, tests were applied to measure the correlation between CO_2 emissions and each independent variable while controlling for the effect of the remaining variables.

Thirdly, using the multiple regression model defined in (3) a stepwise regression analysis quantified the contribution of the various drivers of CO_2 emissions and made it possible to test the hypothesis that GDP_{ppp} per-capita (or 'affluence', g_i) had (or not) the greatest impact. The analysis sequentially assessed the unique impact of each independent variable on CO_2 emissions. If a variable partially explained the behaviour of Y_i (CO_{2i}) it was retained, while all other variables were re-tested to identify whether they were still significant contributors. When a variable no longer contributed significantly to the model, it was removed. This iterative process ran in parallel with multicollinearity tests. The aim was to identify the regression model that explained the greatest part of the variance of CO_2 emissions (i.e. highest *adjusted* R^2), where *p*-values were below 0.10 (for independent variables), the variation coefficient was lowest, and there was no indication of multicollinearity. For the latter, Variance Inflation Factors (VIF) were computed, with a maximum threshold value of five (i.e. a VIF greater than 5, or tolerance levels less than 0.20, were taken as evidence of multicollinearity). Variation coefficients $Coef \quad Var_j = \left(\frac{Std\ error\ estimate_j}{Mean\ value\ CO_{2\,j}}\right)$ of the estimated regression models were also calculated in order to evaluate the variability of the dataset and thus the predictive capability (CO_2 variability) of each regional model. A 10% maximum threshold was set (i.e. Coef Var $_j$ < 10%) and all estimates used a 90% confidence level (unless otherwise stated).

2.3. Measuring the 'Regional Carbon Rebound' effect

Following the various green growth stimulus policy initiatives that were introduced in 2008–2009, we wanted to explore whether (or not) there are early signs that regions have moved towards a green energy (or low-carbon) economy. This is because it has been argued that the global financial crisis provided an opportunity for economies to move away from high carbon emissions. Taken into account the dependent and independent variables mentioned above, the year 2010 was used as the starting point for the regional comparison of recent and historical drivers of CO_2 emissions. The percentage growth rates of CO_2, *TPES*, GDP_{ppp}, *e_int* and *c_int* across all regions were estimated from following formula: $Annual\ growth\ rate\ (in\ \%) = \left(\frac{X_{ni} - X_{n-1i}}{X_{n-1i}}\right) 100$, where X_{ni} is the end of year value of a given variable and X_{n-1i} is the value of a given variable in the previous year. The subscript *i* denotes a given region. Estimates based on this time series data are an update to the trends reported by Mundaca et al. (2013).

3. Results

3.1. Bivariate and partial correlations

The results of bivariate correlation tests are shown in the symmetrical matrices shown in Annex 1. In general, the estimates showed that nearly all independent variables have significant empirical relationships with CO_2 emissions at a regional level. With the exception of OECD Europe (details below), the potential causality between each independent variable and CO_2 emissions was significant. For instance, the correlation between CO_2 and *g* (GDP_{ppp} per capita) was very high, positive and statistically significant in the cases of Asia (99.7%), LATAM (95.3%), Oceania (98.8%) and OECD North America (95.7%). Population was also statistically significant for Africa (98.8%), Asia (93.7%), LATAM (97.3%), the Middle East (99.1%), Oceania (99%) and OECD North America (92.6%). Similarly, *e_int* ($TPES/GDP_{ppp}$) was significant in Asia (−87.1%), Oceania (−91.3%) and OECD North America (−87.7%). However, another important finding was that independent variables were themselves highly correlated (e.g. 95.6% between *Pop* and *g* in Asia; 94.1% between *Pop* and *e_int* in the Middle East; 94.9% between *e_int* and *c_int* in OECD North America), which strongly suggested multicollinearity in the regional regression models.

The OECD Europe region was the notable exception to the results reported above, as none of the variables were statistically significant (i.e. p-values > 0.10) and correlations were low in all cases: *Pop* (6.7%), *g* (13.9%), *e_int* (−3.2%) and *c_int* (−3.5%). Although correlation does not mean causality, these estimates provided an early indication that the independent variables included in the model may not be enough to explain CO_2 emissions in OECD Europe.

Partial correlation tests revealed important, albeit more complex indications of regional drivers or parameters that increased CO_2 emissions. The key findings can be summarised as follows. First, when others variables were controlled, the correlation between CO_2 and *Pop* was statistically significant for Africa (99.1%), LATAM (99.2%), the Middle East (92.5%) and Oceania (66.4%). Compared to bivariate tests, partial correlations for Africa and LATAM marginally increased, suggesting that the correlation between CO_2 and *Pop* was slightly mediated by the other variables. Secondly, the partial correlation between CO_2 and *g* was statistically significant for Africa (97%), Asia (98%), LATAM (98.2%), Non-OECD + FSU (89.3%), Oceania (85.9%) and OECD North America (74.6%). For Africa, this value was much higher than the bivariate test (68.8%). Partialling out other variables individually suggested that *c_int* was the principle mediator, as it showed the lowest correlation with CO_2 (−47.1%) when the effects of *Pop*, *g* and *e_int* were controlled. Thirdly, results for *e_int* and *c_int*, important macro indicators of a GEE, were mixed. Partial correlation estimates were significant for Africa (97% and −47.1%), Asia (64% and 73.4%), LATAM (92.5% and 88.4%), and Non-OECD Europe + FSU (81% and 56.7%). Although significant, partial correlations for the OECD North America region were considered to be (relatively) low (54.1% and −0.27% for *e_int* and *c_int* respectively). With respect to the other regions, *e_int* was not a significant driver for the Middle East but a relevant variable in Oceania (89.6%), and *c_int* was found to be statistically significant in the Middle East (−48.4%) but not in

Oceania and OECD Europe. Other, significant but less powerful correlations were also found (e.g. 27.3% between *CO_2* and *c_int* in OECD North America).

For OECD Europe, partial correlations suggested that only *g* (65.7%) and *e_int* (56.6%) allowed inferences to be potentially drawn about the variability of CO_2 emissions when other variables were controlled. Unlike bivariate tests, these partial correlations strongly suggested that significant relationships between *CO_2* and *g* and *CO_2* and *e_int* were mediated by *Pop* and *c_int*, which turned out to be statistically insignificant when partialled out individually.

3.2. Estimated models

The results of the stepwise multiple regressions are shown in Table 3 and key findings are shown below for each region. In general, and at the risk of oversimplifying, these results show that *g* is a (key) horizontal driver of CO_2 emissions across most regions. Improvements in *e_int* and *c_int* in certain regions do not have the statistical strength to explain changes in CO_2 emissions and do not appear to offset the larger absolute negative effects of economic growth and increased energy use.

Table 3: Regional regressions for the years 1971–2011 and a summary of stepwise modelling outcomes (*p*-values and VIF estimates in parentheses, respectively)

Region	B_0 (Intercept)	β_1 (*Pop*)	β_2 (*g*)	β_3 (*e_int*)	β_4 (*c_int*)	Adjusted R^2	Std error
Africa	-299.64	1.12 (0.00; 1.76)	0.07 (0.04; 1.76)	-	-	0.97	35.75
Asia	-1262.5	-	2.33 (0.00; 1)	-	-	0.99	249.87
LATAM & Caribbean	-564.74	1.77 (0.00; 4.30)	0.09 (0.00; 4.30)	-	-	0.99	22.48
Middle East	-205.93	10.23 (0.00; 1.58)	0.02 (0.00; 1.43)	-	-11.42 (0.00; 1.48)	0.99	38.53
Non-OECD Europe + FSU	-7495.24	-	0.46 (0.00; 2.92)	9427.20 (0.00; 3.55)	44.28 (0.00; 1.49)	0.96	101.43
Oceania	-42.15	-	0.01 (0.00; 1)	-	-	0.97	11.61
OECD Europe	-	-	-	-	-	-	-
OECD North America	2883.49	-	0.10 (0.00; 1)	-	-	0.91	180.88

Results for Africa showed that the best-performing model was the one in which *Pop* and *g* were the main predictors of *CO_2* (F = 876.6; *p*-value = .000 [i.e. $p < 0.1$]). The adjusted R^2 indicated that approximately 98% of the variability of CO_2 emissions in Africa could be explained by *Pop* and *g*. Other independent variables only contributed marginally to a better goodness-of-fit (e.g. < 1.5%) and further statistical tests (e.g. collinearity) showed that these variables were irrelevant. Estimated coefficients showed that *Pop* had the greatest impact on the average change in *CO_2* emissions when *g* is held constant. The coefficient of variation of this estimated regression model ($Coef\_Var_{reg\_Africa}$ = Std. error estimate [± 35.75]/ mean CO_2 emissions [627.67 $MtCO_2$]) was 5.69%, which suggested that the estimated model that included *Pop* and *g* as key independent variables was useful in predicting CO_2 emission interval values, as the estimated ratio was lower than the 10% maximum allowed threshold. Collinearity statistics revealed no evidence of correlation among predictors.

In Asia, the statistical strength of *g* as a key predictor was clearer than any of the other tested variable(s) (F = 6745.7; *p*-value = .000). The stepwise analysis lead to an adjusted R^2 of 0.994, which indicated that approximately 99% of the variability of *CO_2* emissions was explained solely by *g*. For this single predictor, the estimated coefficient of variation in the Asian model was 4.18%, lower than the 10% allowed threshold. Although statistically significant, when *e_int* and *c_int* were introduced into the original model their contribution to the adjusted goodness-of-fit was marginal (< 0.4%) and caused multicollinearity problems (VIF > 5). Contrary to our early expectations (from bivariate tests), the regression showed that *Pop* played no statistically significant role in explaining changes in CO_2 emissions in Asia in the period under analysis.

The case for LATAM turned out to be similar to that of Africa; *Pop* and *g* explained 99% of the variability of CO_2 emissions. The $Coef\_Var_{reg\_LATAM}$ was 3.14% (i.e. < 10%), suggesting that large fluctuations in CO_2 emissions could be explained by the estimated model. This model (Model 1_LATAM) performed slightly better than another statistically significant model that was tested, in which *Pop* and *e_int* (Model 2_LATAM) also played important roles as predictors. The standard error was slightly higher in Model 2_LATAM (±42.8 $MtCO_2$) and thus the adjusted R^2 was lower (96.2%) than in Model 1_LATAM. No multicollinearity problems were identified in either model (i.e. VIF < 5).

As for the Middle East, the stepwise regression approach showed that *Pop*, *g* and *c_int* were significant variables that explained 99.2% of changes in CO_2 emissions in the region ($F = 1695.6$; $p = .000$). Consistent with the region's oil dependency (Grubler et al. 2012), *c_int* turned out to be a significant predictor. When *e_int* was introduced as explanatory variable, its contribution to the model was irrelevant and led to serious multicollinearity problems. Of all of the Middle Eastern models, the set of predictors *Pop*, *g* and *c_int* had the lowest standard error (± 38.53 $MtCO_2$) and VIF (around 1.5). Used predictively, this model was able to explain large CO_2 fluctuations for the period 1971–2011, with an estimated $Coef\_Var_{reg\_Middle\_East}$ equivalent to 5.55%.

For the Non-OECD+FSU region, estimates and tests suggested that the model based on *g*, *e_int* and *c_int* as predictors showed the most significant relationships ($F = 403.9$; p-value = .000). These independent variables explained up to 96.8% of variability in CO_2 emissions for this region, with *e_int* as the most influential predictor. Four other models did not have multicollinearity problems, and this set of predictors had the lowest standard error (± 101.43 $MtCO_2$) and the lowest $Coef\_Var_{reg\_Non\_OECD+FSU}$ (3.21%). Overall, and despite the sudden decline in CO_2 emissions that characterised post-Soviet states in the 1990s, the results of this regression seem to be consistent with the economic (and energy use) transition that took place in the region.

Concerning Oceania, *g* turned out to be the single significant driver of CO_2 emissions. The growth of GDP_{ppp} per capita (or 'affluence') in Oceania explained up to approximately 98% of the variability of CO_2 emissions, and thus there is relatively little fluctuation that cannot be explained by the dataset (approximately 3.96%). Similarly, results for OECD North America showed that *g* explained most of the fluctuation in CO_2 emissions (91.3%). From a *regional* perspective and taking into account the study's limitations (e.g. observations from *different* countries are pooled into one region), these results do not support the so-called 'Environmental Kuznets Curve' (EKC) hypothesis (see e.g. Barbier 1997). This hypothesis states that as per capita income grows, environmental pollution (in our case CO_2 emissions) increase to a maximum and then decline, indicating an inverted U-shaped relationship between GDP per capita and CO_2 emissions.

For OECD Europe the results were inconclusive. Consistent with correlation tests, the model did not indicate any statistically significant relationship(s). None of the independent variables had the strength to explain variability in CO_2 emissions. When explanatory variables were "forced" into the model, the results were unconvincing (e.g. adjusted $R^2 = -25\%$) and clearly statistically insignificant (e.g. p-values for *e_int* = 0.84). Although further work may demonstrate reliable outcomes (e.g. an alternative functional form or a non-parametric approach), we note that our results appear to be consistent with regression analyses (parametric and non-parametric) that have found mixed evidence of the relationship between CO_2 emissions and *g* (regardless of data source) in the region[2]. Taking the case of a single country regression analysis, which reduces the potential bias caused by pooling data from different countries into one region (i.e. 'regional homogeneity'), results diverge (e.g. positive correlations, stabilising patterns) and autocorrelation problems remain even if other explanatory variables (e.g. population) are included (Dijkgraaf and Vollebergh 1998). Although an alternative (Weibull) functional form may yield estimates that are consistent with the EKC hypothesis in some European OECD countries (Galeotti, Lanza, and Pauli 2006), single country analyses have shown that neither a 'U-inverted' relationship between CO_2 and *g*, nor the third order polynomial 'N'-

[2] For a review of studies about EKC and CO_2 emissions see Galeotti et al. (2006).

shaped relationship between CO_2 emissions and income enable reliable inferences to be made for more than 10 OECD countries (Moomaw and Unruh 1997).

3.3. The 'Carbon Rebound' effect

Overall, our results show that the 2010 'Carbon Rebound' effect was much more pronounced in certain regions; it was neither a global scale phenomenon, nor was it confined to less industrialised countries (see Figure 1).

Regions that did show a pronounced carbon rebound effect were LATAM, Non-OECD Europe + FSU, OECD Europe and OECD North America. In these regions, estimates showed that emission growth hit a record high in 2010 compared to their historical averages and the rebound effect quickly offset the 2008–2009 emission reductions during the global financial crisis (e.g. −6.6% in OECD Europe and −9.6% in Non-OECD Europe + FSU). The emission surge correlated directly with increased economic activity (GDP_{ppp}) and energy supply (TPES) (see Table 4) (c.f. Jotzo et al. 2012; Mundaca, Markandya, and Nørgaard 2013). For both OECD and Non-OECD Europe regions, the historical decline in energy intensity not only stopped, but the trend reversed (e.g. +1.8% in OECD Europe). However, estimates suggest that OECD Europe is the only region that has been making consistent progress in decarbonising its energy mix. Although there was a decrease in energy intensity in OECD North America (−0.6%) in 2010, recent figures show a slight weakening of a historically relatively strong decline (−1.8%). In addition, the CO_2 intensity of its energy supply mix has increased. Of these four regions, Non-OECD Europe + FSU experienced the highest rebound in emissions in 2010 (from −9.6% in 2009 to +8.2% in 2010). This was despite the fact that the region showed progress in decarbonising its energy mix. Nevertheless, our estimates showed that progress in reducing energy intensity has slowed and the trend has reversed. In the LATAM region emissions grew much faster than both GDP_{ppp} and TPES, which grew more than twice (7.1%) its average historical rate (2.9%). Estimates indicated that there was no improvement in energy and CO_2 intensities, which confirmed the historical lack of progress.

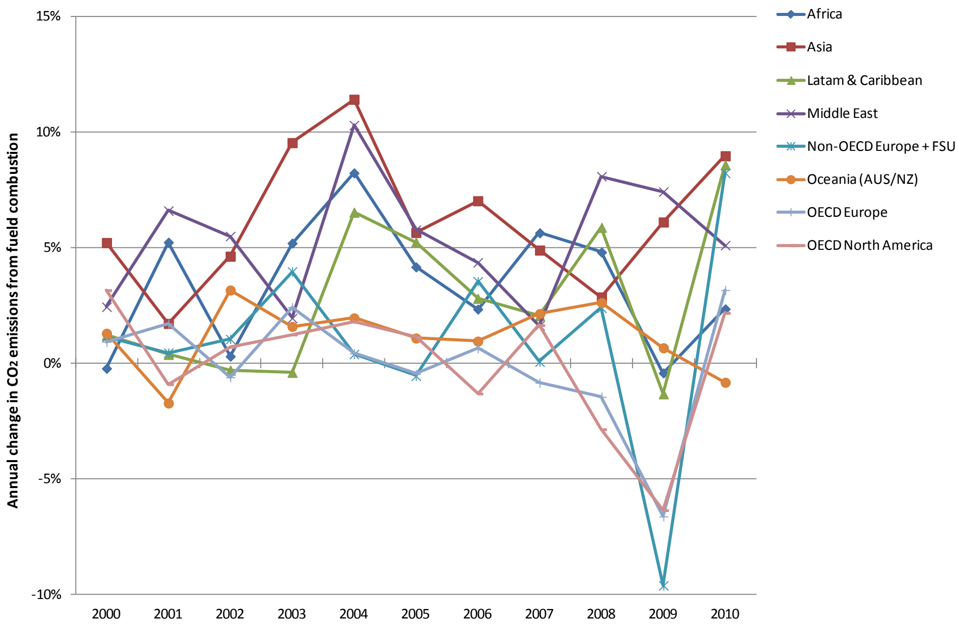

Figure 1: Regional decomposition of annual change in CO_2 emissions from fuel combustion 2000–2010

In Asia (and to some extent Africa) there were signs of a rebound effect; however emission reductions in 2008–2009 were less pronounced than the regions mentioned above and the annual change remained positive. Asia, which has been the world's highest CO_2 emitter since the mid-1990s (see Figure 2), showed record growth in emissions in 2010 (+9%); a rate that was much higher than historical annual averages. Like LATAM, emissions in Asia grew faster than energy use and GDP_{ppp}. In addition, the region did not show any progress in the decarbonisation of its energy supply mix; CO_2 intensity rates also reached record levels. Estimated *absolute* figures revealed a distressing, marked, upward historical trend: 51.3 tCO_2/TJ in 1971, 56.9 tCO_2/TJ in 1990, and 66.2 tCO_2/TJ in 2010. Although energy intensity in 2010 decreased by 0.4%, the improvement was primarily due to an increase in economic activity (8.3%) rather than reductions in energy use.

Table 4: Regional decomposition of CO_2 emissions. All figures are in precentages (%) and represent annual changes

Annual % changes in	Africa	Asia	Latam & Caribb	Middle East	Non-OECD Europe & FSU	Oceania	OECD Europe	OECD North America
CO_2 emissions								
2010	2,4%	9,0%	8,6%	5,1%	8,2%	-0,8%	3,2%	2,2%
1972-2011 average	3,8%	4,9%	3,0%	7,0%	0,3%	2,2%	0,1%	0,7%
Decadal averages								
1972-1980	5,7%	4,9%	5,0%	12,3%	3,7%	3,3%	1,5%	1,6%
1981-1990	4,1%	4,5%	1,0%	6,1%	1,4%	2,2%	-0,4%	0,3%
1991-2000	2,0%	3,6%	3,3%	5,3%	-4,9%	2,5%	-0,1%	1,6%
2001-2010	3,8%	6,3%	2,9%	5,7%	1,0%	1,2%	-0,2%	-0,3%
Energy (TPES)								
2010	2,8%	7,9%	7,1%	5,3%	8,3%	0,9%	4,3%	2,1%
1972-2011 average	3,2%	4,2%	2,9%	7,1%	0,9%	2,2%	0,9%	1,0%
Decadal averages								
1972-1980	4,0%	4,3%	4,2%	11,5%	4,2%	3,4%	2,1%	1,9%
1981-1990	3,5%	3,9%	1,7%	6,6%	2,2%	2,4%	0,8%	0,8%
1991-2000	2,5%	3,3%	2,8%	5,5%	-4,1%	2,4%	0,8%	1,7%
2001-2010	3,3%	5,1%	3,1%	6,0%	1,3%	1,2%	0,4%	-0,1%
GDP_{ppp}								
2010	4,8%	8,3%	6,2%	5,0%	4,0%	2,2%	2,5%	2,7%
1972-2011 average	3,3%	5,5%	3,4%	3,3%	2,0%	3,0%	2,4%	2,9%
Decadal average								
1972-1980	3,9%	5,2%	5,4%	7,2%	5,2%	2,7%	3,2%	3,6%
1981-1990	2,1%	5,9%	1,3%	-1,5%	1,5%	2,9%	2,5%	3,1%
1991-2000	2,5%	4,8%	3,1%	3,3%	-3,7%	3,5%	2,3%	3,4%
2001-2010	4,9%	6,0%	3,9%	4,5%	5,1%	3,0%	1,6%	1,6%
CO_2/TPES								
2010	1,4%	1,0%	1,4%	-1,1%	-1,6%	-1,7%	-1,1%	0,1%
1972-2011 average	0,2%	0,6%	0,1%	0,2%	-0,3%	-0,1%	-0,8%	-0,3%
Decadal averages								
1972-1980	1,5%	0,6%	0,7%	1,9%	0,5%	0,0%	-0,6%	-0,3%
1981-1990	-0,4%	0,5%	-0,7%	-0,2%	-0,6%	-0,2%	-1,3%	-0,5%
1991-2000	-0,2%	0,3%	0,5%	-0,3%	-0,8%	0,1%	-0,7%	-0,1%
2001-2010	0,3%	1,1%	-0,2%	-0,5%	-0,4%	0,0%	-0,6%	-0,2%
Energy/GDP_{ppp}								
2010	-2,0%	-0,4%	0,8%	0,3%	4,1%	-1,3%	1,8%	-0,6%
1972-2011 average	0,0%	-1,2%	-0,5%	4,0%	-1,0%	-0,7%	-1,4%	-1,8%
Decadal averages								
1972-1980	0,0%	-0,8%	-1,2%	4,3%	-0,8%	0,7%	-1,0%	-1,7%
1981-1990	1,4%	-1,9%	0,5%	8,8%	0,7%	-0,5%	-1,6%	-2,3%
1991-2000	0,0%	-1,4%	-0,2%	2,2%	-0,2%	-1,1%	-1,5%	-1,6%
2001-2010	-1,6%	-0,8%	-0,8%	1,5%	-3,6%	-1,8%	-1,2%	-1,6%

Regarding the other regions, results were mixed. In Africa the growth in emissions was slower than both GDP_{ppp} and TPES (with the exception of the years 1991–2000). Despite a significant improvement in energy intensity (−2% in 2010), the carbonisation of its energy mix was similar to the period 1972–1980. However, our results showed that Africa has made consistent reductions in energy intensity since the mid-1990s and is still a relatively marginal global contributor to CO_2

emissions (Figure 2). Oceania was the only region with decreased emissions in 2010. This was despite the fact that the region experienced an increase in economic activity. Only this region showed a simultaneous reduction in energy and CO_2 intensities. However, although there was a relative decrease in CO_2 intensity of 1.7% (historically the lowest annual change rate), there was no significant *absolute* historical progress, and Oceania's CO_2 intensity has been the highest in the world for the past three decades (69.2 tCO_2/TJ). Finally, the Middle East region did not experience a carbon rebound effect in the immediate post-financial crisis period. Although emissions grew slightly faster than GDP_{ppp} and TPES in 2010, this was slower than historical rates (the highest rate across all regions, see Table 4). Additionally, although energy intensity in 2010 increased more slowly (0.3%) than the historical annual average (4%), absolute values showed a very disturbing upward trend. In fact, the Middle East recorded the most dramatic increase in energy intensity (by a factor of five) than any other region in the world historically.

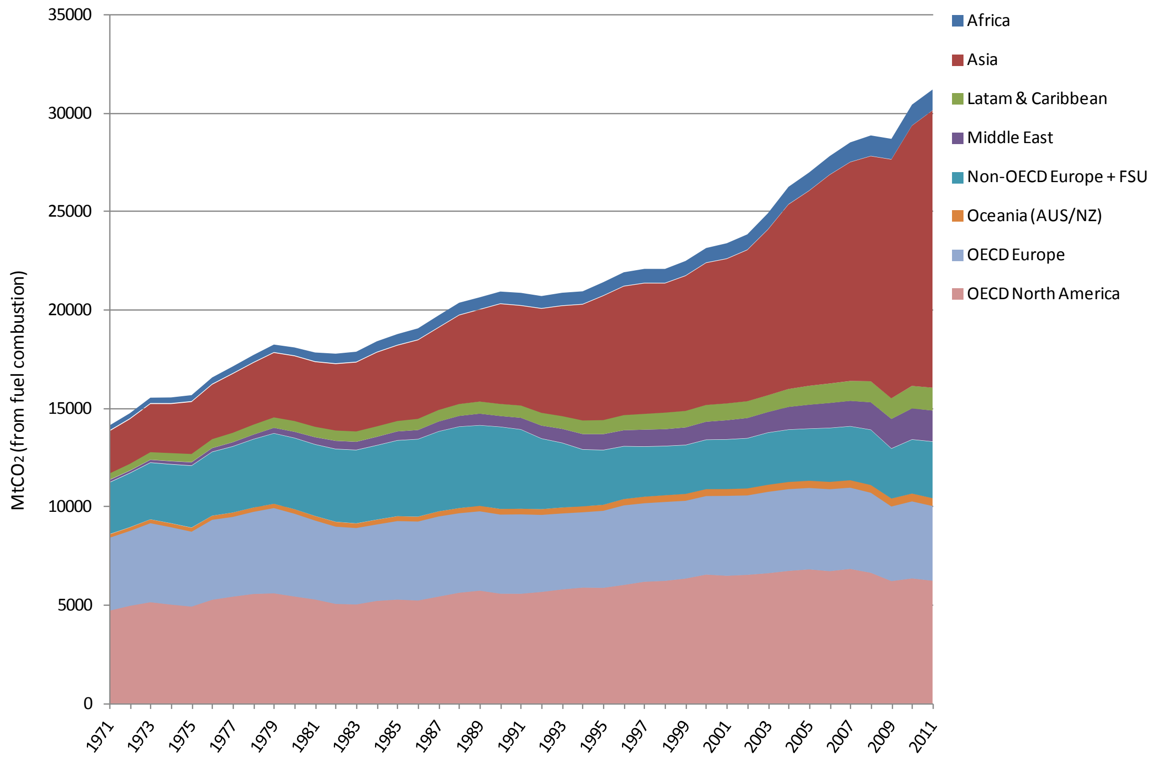

Figure 2: CO_2 emissions from fuel combustion for eight regions of the world for the years 1971–2011

4. Conclusions

This paper provided the first *regional* econometric decomposition of CO_2 emissions. The aim was to quantitatively analyse the extent of progress towards a Green Energy Economy (GEE). Using the best publically-available time series data, the method and analysis focused on the key aspects of a GEE, namely, economic growth, energy intensity (a macro indicator of energy efficiency), CO_2 intensity (a macro indicator of a low-carbon energy supply) and CO_2 emissions from fuel combustion (the dominant anthropogenic greenhouse gas [GHG] flux).

Overall, our results show that from a regional perspective, region have made variable progress towards a GEE. Using CO_2 as an entry point for the analysis, our estimates clearly show that emissions continue to grow across most regions (annual growth in the range of 0.1–7.0%) although the last decade has seen some declines in OECD Europe and OECD North America. It seems therefore that another opportunity has been missed to limit this type of GHG. When estimates were based on energy intensity or CO_2 intensity (as indicators of a GEE), some progress was identified in certain regions (e.g. reduced energy intensity in Asia, lower carbon intensity in OECD Europe). However, this *relative* progress has not offset the effects of economic growth and energy use. In fact GDP_{ppp} per capita, or *affluence*, was found to be a (significant) key driver of accelerating CO_2 emissions in most regions. In other cases, there was no evidence of even relative progress (e.g. growing energy intensity in the Middle East). Our estimates revealed that in recent times the performance of most regions is worse than historical trends. Our figures suggest that the opportunity to reduce carbon dependency, created by the 2008–2009 global financial crisis, was missed.

From a modelling perspective, the regional model and subsequent tests provided useful insights into the principal relationships and drivers of CO_2 emissions and some key aspects of a GEE at a regional level. In cases where there was a sharp decrease in CO_2 emissions (e.g. Non-OECD Europe + FSU region, and the years 2008–2009 for most regions), CO_2 emissions did not appear to correlate with either income or other explanatory variables included in the model, but rather to a historical exogenous shock to regional economies (e.g. the global financial crisis). In the particular case of the relationship between CO_2 emissions and GDP per capita, our findings do not support the EKC hypothesis in Oceania and OECD North America. Our results were unconvincing for OECD Europe and seem to indicate that the model needs refinement if it is to be applied to this region (e.g. non-parametric approaches or an alternative regression function). Moreover, further examination of other (potential) explanatory variables is necessary (e.g. energy prices). The fact that single country data was pooled implied that the outcome of the socio-economic and energy development process is relatively homogeneous across all OECD European countries with respect to CO_2 emissions. This underlying assumption is open to challenge and the more common single-country analytical approach may be more suitable for this region. However, our literature review showed that single country regression analyses do not seem to provide more robust results for OECD countries.

From a policy perspective, our analysis indicates that CO_2 emissions may fall in the future in Europe and North America if countries in these regions show similar rates of decarbonisation as in the past. To achieve the target of an 80% reduction by 2050, aggressive and highly ambitious energy efficiency and renewable energy policies need to be implemented. Clear policy commitments and meaningful behavioural change across all regions are needed. Policies to reduce fossil fuel-based energy use and CO_2 emissions in absolute terms are urgently needed in rich regions. This would leave room for economic development in less-developed regions, where the needs are apparent.

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Annex 1: Bivariate correlation tests

Africa		CO_2	Pop	g	e_int	c_int
CO_2	Correlation	1	.988	.688	.151	-.122
	p-value		.000	.000	.173	.223
	N	41	41	41	41	41
Pop	Correlation	.988	1	.658	.130	-.158
	p-value	.000		.000	.209	.163
	N	41	41	41	41	41
g	Correlation	.688	.658	1	-.572	.247
	p-value	.000	.000		.000	.060
	N	41	41	41	41	41
e_int	Correlation	.151	.130	-.572	1	-.339
	p-value	.173	.209	.000		.015
	N	41	41	41	41	41
c_int	Correlation	-.122	-.158	.247	-.339	1
	p-value	.223	.163	.060	.015	
	N	41	41	41	41	41

Asia		CO_2	Pop	g	e_int	c_int
CO_2	Correlation	1	.937	.997	-.871	.992
	p-value		.000	.000	.000	.000
	N	41	41	41	41	41
Pop	Correlation	.937	1	.956	-.980	.951
	p-value	.000		.000	.000	.000
	N	41	41	41	41	41
g	Correlation	.997	.956	1	-.902	.990
	p-value	.000	.000		.000	.000
	N	41	41	41	41	41
e_int	Correlation	-.871	-.980	-.902	1	-.889
	p-value	.000	.000	.000		.000
	N	41	41	41	41	41
c_int	Correlation	.992	.951	.990	-.889	1
	p-value	.000	.000	.000	.000	
	N	41	41	41	41	41

Latin America & Caribbean		CO_2	Pop	g	e_int	c_int
CO_2	Correlation	1	.973	.953	-.785	-.102
	p-value		.000	.000	.000	.262
	N	41	41	41	41	41
Pop	Correlation	.973	1	.876	-.713	-.236
	p-value	.000		.000	.000	.069
	N	41	41	41	41	41
g	Correlation	.953	.876	1	-.905	-.033
	p-value	.000	.000		.000	.419
	N	41	41	41	41	41
e_int	Correlation	-.785	-.713	-.905	1	-.042
	p-value	.000	.000	.000		.397
	N	41	41	41	41	41
c_int	Correlation	-.102	-.236	-.033	-.042	1
	p-value	.262	.069	.419	.397	
	N	41	41	41	41	41

Middle East		CO_2	Pop	g	e_int	c_int
CO2	Correlation	1	.991	-.421	.901	-.549
	p-value		.000	.003	.000	.000
	N	41	41	41	41	41
Pop	Correlation	.991	1	-.505	.941	-.531
	p-value	.000		.000	.000	.000
	N	41	41	41	41	41
g	Correlation	-.421	-.505	1	-.734	.454
	p-value	.003	.000		.000	.001
	N	41	41	41	41	41
e_int	Correlation	.901	.941	-.734	1	-.531
	p-value	.000	.000	.000		.000
	N	41	41	41	41	41
c_int	Correlation	-.549	-.531	.454	-.531	1
	p-value	.000	.000	.001	.000	
	N	41	41	41	41	41

Non-OECD+FSU		CO_2	Pop	g	e_int	c_int
CO_2	Correlation	1	.069	.456	.197	.626
	p-value		.333	.001	.109	.000
	N	41	41	41	41	41
Pop	Correlation	.069	1	.213	-.041	-.641
	p-value	.333		.091	.399	.000
	N	41	41	41	41	41
g	Correlation	.456	.213	1	-.764	-.079
	p-value	.001	.091		.000	.311
	N	41	41	41	41	41
e_int	Correlation	.197	-.041	-.764	1	.428
	p-value	.109	.399	.000		.003
	N	41	41	41	41	41
c_int	Correlation	.626	-.641	-.079	.428	1
	p-value	.000	.000	.311	.003	
	N	41	41	41	41	41

Oceania		CO_2	Pop	g	e_int	c_int
CO_2	Correlation	1	.990	.988	-.913	.055
	p-value		.000	.000	.000	.367
	N	41	41	41	41	41
Pop	Correlation	.990	1	.989	-.938	.011
	p-value	.000		.000	.000	.473
	N	41	41	41	41	41
g	Correlation	.988	.989	1	-.960	.110
	p-value	.000	.000		.000	.246
	N	41	41	41	41	41
e_int	Correlation	-.913	-.938	-.960	1	-.159
	p-value	.000	.000	.000		.161
	N	41	41	41	41	41
c_int	Correlation	.055	.011	.110	-.159	1
	p-value	.367	.473	.246	.161	
	N	41	41	41	41	41

OECD Europe		CO_2	Pop	g	e_int	c_int
CO_2	Correlation	1	.067	.139	-.032	-.035
	p-value		.338	.193	.422	.415
	N	41	41	41	41	41
Pop	Correlation	.067	1	.990	-.995	-.978
	p-value	.338		.000	.000	.000
	N	41	41	41	41	41
g	Correlation	.139	.990	1	-.988	-.963
	p-value	.193	.000		.000	.000
	N	41	41	41	41	41
e_int	Correlation	-.032	-.995	-.988	1	.980
	p-value	.422	.000	.000		.000
	N	41	41	41	41	41
c_int	Correlation	-.035	-.978	-.963	.980	1
	p-value	.415	.000	.000	.000	
	N	41	41	41	41	41

OECD North America		CO_2	Pop	g	e_int	c_int
CO_2	Correlation	1	.926	.957	-.877	-.787
	p-value		.000	.000	.000	.000
	N	41	41	41	41	41
Pop	Correlation	.926	1	.990	-.981	-.930
	p-value	.000		.000	.000	.000
	N	41	41	41	41	41
g	Correlation	.957	.990	1	-.967	-.887
	p-value	.000	.000		.000	.000
	N	41	41	41	41	41
e_int	Correlation	-.877	-.981	-.967	1	.949
	p-value	.000	.000	.000		.000
	N	41	41	41	41	41
c_int	Correlation	-.787	-.930	-.887	.949	1
	p-value	.000	.000	.000	.000	
	N	41	41	41	41	41