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Dinda, Soumyananda and Coondoo, Dipankor

S.R.Fatepuria College, Beldanga, Murshidabad, India, Economic Research Unit, Indian Statistical Institute, Kolkata, India

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SOUMYANANDA DINDA

S. R. Fatepuria College, Beldanga, Murshidabad, W.B., India.

Economic Research Unit, Indian Statistical Institute, Kolkata-108. India.

DIPANKOR COONDOO*

Economic Research Unit, Indian Statistical Institute, Kolkata-108. India.

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Abstract

This paper presents the results of an investigation of the causality issue of income-emission relationship based on time series econometric techniques of unit root test, co-integration and related error correction model for a panel data set. Here, the nature of causality between per capita CO_2 emission (*PCCO2*) and per capita GDP (*PCGDP*) has been examined using a cross country panel data set covering 88 countries for the period 1960 - 90. Using the panel unit root test procedure of Im et al. (1997) (*IPS*), we have found that the hypothesis of unit root (i.e., non-stationarity) of the time series of *PCGDP* and *PCCO2* can not be rejected for individual country groups. As both the variables are found to follow I(1) process, we next have performed the panel data co-integration test and finally, we have estimated the *ECM* (for these country groups for which significant income-emission cointegration was obtained) to explore the nature of dynamics implicit in the given panel data set. Our findings suggest that there is more or less a bi-directional causal relationship between income (*PCGDP*) and CO_2 emission (*PCCO2*) for Africa, Central America, America as a whole, Eastern Europe, Western Europe, Europe as a whole and the World as a whole. That means, the movement of the one variable directly affects the other variable through a feedback system. Thus, the policy makers should be cautious to make proper decision about the control of emission level.

JEL *Classification*: C33, O40, and Q25.

Keywords: Panel data, Unit Root, *IPS*, CO_2 emission, *GDP*, co-integration, causality, *ECM*.

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*Corresponding Author: Soumyananda Dinda, c/o, Dipankor Coondoo, Economic Research Unit, Indian Statistical Institute, 203, B. T. Road, Kolkata-108, India. E-mail: s_dinda@hotmail.com and sdinda2000@yahoo.co.in , dcoondoo@isical.ac.in (D. Coondoo), Fax No: 91-033-577-8893.

1. **Introduction**

Coondoo and Dinda (2002) examined the nature of causality between CO_2 emission and income using a cross-country panel data set covering 88 countries and the time period 1960-90. Briefly, in that study the presumption of the *Environmental Kuznets Curve (EKC)* hypothesis – viz., that an income to pollution (CO_2 emission, more specifically) causal relationship holds universally – was examined. However, the results based on the Granger causality test (*GCT)* did not lend much empirical support to that presumption. Instead, for individual country groups well-defined and distinctive patterns of causality were observed. For example, for the developed country groups of North America and Western Europe (and for that matter, East Europe also), causality was found to run from emission to income. For Japan, the developing country groups of Central and South America and Oceania, on the other hand, causality in the opposite direction was observed. Finally, for country groups of both Asia and Africa causality turned out to be bi-directional[1]. Interpretation of these observed causality patterns was given in terms of inter-temporal changes in the rates of growth of income and emission. This interpretation made it clear how shocks in the rate of growth of income or emission might affect each other depending on the prevailing nature of causality.

The *GCT* has been used in many empirical studies on *EKC* and related issues[2]. This technique alone, however, can detect presence and direction of causality for a pair of variables only in a limited sense (viz., in respect of their short run temporal movements). The notion of causality between income growth and pollution that underlies the *EKC*

[1] A closer examination of the country-wise data for Asia and Africa revealed that while some countries had causality in one direction, others had causality in the opposite direction. Possibly this heterogeneity in the pattern of causality led to the observed bi-directional causality at the level of country-groups for these two continents.
[2] See, e.g., Yu and Choi (1985), Cheng (1996), Cheng and Lai (1997) and Yang (2000).

hypothesis, on the other hand, is essentially a longer run concept[3]. Thus, further probe into the issue of causality using comprehensive econometric tools for exploring presence of any long run equilibrium relationship among income and pollution, viz., the co-integration analysis, may help verify conclusions about causality that we have reached so far[4].

In this paper, we report the results of an analysis of the relationship between per capita *GDP (PCGDP)* and per capita CO_2 emission *(PCCO2)* obtained by using non-stationary panel data techniques to a cross-country panel data set on these variables. For convenience of exposition, henceforth we shall call these variables *income* and *emission*, respectively. To be precise, here we first used the *panel data unit root test* procedure of Im, Pesaran and Shin (1997) (henceforth referred to as IPS) to examine whether the observed country-specific time series data on income and emission possessed stochastic trend or not. Next, on finding evidences of presence of such trend in the data set, we performed the Engle-Granger bivariate cointegration analysis[5] to examine whether the pair of variables was cointegrated (i.e., whether they obeyed any long run equilibrium relationship between themselves). Finally, we estimated the *Error Correction Model (ECM)* for those country groups for which income-emission cointegration was obtained to explore the nature of dynamics implicit in the panel data set for those country groups.

[3] See, Coondoo and Dinda (2002) for a discussion on this issue.
[4] There are interesting applications of time series econometric tools like vector autoregression model (VAR) and cointegration analysis on environment-related data. See, e.g., Stern (1993, 2000) for studies on causal relationship between GDP and energy use for the USA for the period 1947-1990 based on *GCT* in a VAR set up, single equation static co-integration analysis and multivariate dynamic co-integration analysis. See also Cheng (1999) for an application of Johansen co-integration test to the data on energy consumption, economic growth, capital and labour for the Indian economy.
[5] Johansen's method of cointegration analysis, which is more comprehensive, could not be used, because we could not access software for application of Johansen's method to panel data set.

The paper is organized as follows: section 2 explains the motivation for using cointegration analysis on the income-emission data in the present exercise; section 3 describes the data, presents and discusses the empirical results, section 4 interprets the results and section 5 draws some concluding observations. Finally, the methodology of unit root test, cointegration analysis and *ECM* estimation based on panel data that we have actually used in the present exercise is briefly explained in the Appendix.

2. **Motivation**

To help justify the use of cointegration analysis on the set of cross-country panel data on income and emission for examining the nature of causality that may exist between this pair of variables, let us consider the following simple theoretical construct. Consider a one-good economy for which environment E, understood as a stock variable, affects both utility and production level of the representative agent. Let $C(t)$, $E(t)$ and $K(t)$ denote consumption, environment and capital stock at time t . Let $\theta(t)$ $(0<\theta(t)<1)$ portion of capital stock be used for commodity production at time t and the remaining $(1-\theta(t))$ portion be used for upgrading the environment. Finally, let $\gamma\,(>0)$ be the rate of pollution (i.e., emission or degradation of environment per unit of output produced). The infinite time horizon inter-temporal consumption choice problem for this economy may be specified as

$$\text{Maximize } W = \int_0^\infty e^{-\rho t} U(C(t), E(t))dt \qquad (1)$$

subject to the accumulation constraints

$$\dot{K}(t) = f(\theta(t)K(t), E(t)) - C(t) \qquad (2)$$

and

$$\dot{E}(t) = g((1-\theta(t))K(t), E(t)) - \gamma f(\theta(t)K(t), E(t)) \qquad (3)$$

where $\rho > 0$ is the rate of time preference and *f(.)* and *g(.)* are the production function and the *environment upgrading* function of the economy. Clearly, the first constraint relates to physical capital accumulation while the second relates to net environmental change due to production and environmental upgrading. Treating *C(t)* and θ *(t)* as control variables and *K(t)* and *E(t)* as state variables, the optimality condition for the above problem turns out to be

$$\alpha \frac{\dot{C}}{C} + \beta \frac{\dot{E}}{E} = \phi \qquad (4)$$

where $\alpha = \frac{CU_{CC}}{U_C}$, $\beta = \frac{EU_{CE}}{U_C}$ and $\phi = (-\frac{f_K g_K}{g_K + \gamma f_K} + \rho)$, U_{CC}, U_{CE} being the second order partial derivatives of $U(.)$. Note that the above condition suggests that optimal time path of *C* and *E* should generally be interdependent. This, thus, means a two-way causal relationship between income and emission, in general. If, however, $\alpha(\beta)$ turns out to be identically zero, the optimal time path of *C* (*E*) will be autonomous and the nature of the optimal time path of *E* (*C*) will depend upon what the optimal path of the other variable is.

Let us next search for a long run equilibrium relationship between income (*C*) and emission (*E*), underlying the above optimization problem. To do so, consider the *steady state solution* where $\dot{E} = \dot{\mu} = 0$ i.e., the situation where the environmental stock reaches a stable level. Now, $\dot{E} = 0$ implies

$$g((1-\theta)K, E) = \gamma f(\theta K, E) \qquad (5)$$

i.e., the rate of environmental degrading due to production must equal the rate of environmental upgrading. Clearly, eq.(5) defines a relationship between *K* and *E* – say,

$$h_1(K, E) = 0, \tag{6}$$

for given θ. Next, let at the steady state $\dot{K} = \sigma$, a constant. This implies

$$f(\theta K, E) - C = \sigma \Rightarrow h_2(K, E, C) = 0, \tag{7}$$

for given θ. Combining eq.s (6) and (7), we obtain what may be called a long run equilibrium relationship between *C* and *E*, say,

$$h_3(C, E) = 0 \text{, or equivalently, } E = h(C), \tag{8}$$

which may be recognized as the long run relationship between income (C) and environment (E).

It should now be straightforward to use the above theoretical construct to rationalize cointegration analysis of a bivariate time series/panel data set on income and emission, as we have done in the present paper. Let $\{C_t^*, E_t^*\}$ denote time series of observed consumption and environment variable, where $C_t^* = C_t + \varepsilon_{Ct}$ and $E_t^* = E_t + \varepsilon_{Et}$ - C_t, E_t being corresponding (unobserved) optimal values and $\varepsilon_{Ct}, \varepsilon_{Et}$ being random disturbances. In case the observed data set is consistent with optimization, C_t^* and E_t^* should differ from the corresponding optimal values only by stationary random disturbances (i.e., ε_{Ct} and ε_{Et} should be stationary random variables). Also, C_t^* and E_t^*, being consistent with optimization, should be *cointegrated* as they must obey eq. (8), but for stationary deviations.

Granger causality between *C* and *E*, which is essentially a short run notion, is often examined with the help of the *ECM* as a part of the cointegration analysis. When time series C_t^* and E_t^* are non-stationary and are integrated of order one (i.e., the corresponding time series of first differences are stationary) and the variables are cointegrated, they admit the *Granger representation*[6] and the *ECM* can be expressed as

$$\Delta C_t^* = \sum_{i=1}^{m} \beta_{Ci} \Delta C_{t-i}^* + \sum_{i=1}^{m} \gamma_{Ci} \Delta E_{t-i}^* - \eta_C (E_{t-1}^* - h(C_{t-1}^*)) + \nu_{Ct} \tag{9}$$

or, equivalently as

$$\Delta E_t^* = \sum_{i=1}^{m} \beta_{Ei} \Delta C_{t-i}^* + \sum_{i=1}^{m} \gamma_{Ei} \Delta E_{t-i}^* - \eta_E (E_{t-1}^* - h(C_{t-1}^*)) + \nu_{Et} \tag{10}$$

where ν_{Ct} and ν_{Et} are pure white noise random disturbances and $\beta_{Ci}, \beta_{Ei}, \gamma_{Ci}, \gamma_{Ei}, \eta_C$ and η_E are the parameters of the *ECM*. Note that $(E_{t-1}^* - h(C_{t-1}^*))$, which is called the *error correction term,* is a measure of the extent by which the observed values in time *t-1* deviate from the long run equilibrium relationship. Since the variables are cointegrated, any such deviation at time *t-1* should induce changes in the values of the variables in the next time point in an attempt to force the variables back to the long run equilibrium relationship. The coefficients η_C and η_E of the error correction term in the two equations (which measure the rate of this adjustment process) are therefore called the *adjustment parameters* and are expected to be positive. The parameters γ_{Ci}'s in eq. (9) and β_{Ei}'s in eq. (10) determine the nature of causality between *C* and *E*. More specifically, if $\gamma_{Ci} \neq 0$ for at least one $i (i = 1, m)$ and $\beta_{Ei} = 0$ for all $i (i = 1, m)$, then *E* is said to *Granger cause* C. On the other hand, if $\gamma_{Ci} = 0$ for all $i (i = 1, m)$ and $\beta_{Ei} \neq 0$ for at least one $i (i = 1, m)$, then *C* is said to *Granger cause E*. In case $\gamma_{Ci} \neq 0$ and $\beta_{Ei} \neq 0$ for at least one $i (i = 1, m)$,

[6] See Hamilton (1994) for details.

the causality between C and E is defined to be bi-directional. Finally, when $\gamma_{Ci} = 0$ and $\beta_{Ei} = 0$ for all $i(i = 1, m)$, Granger causality between C and E is said to be absent[7]. The absence of Granger Causality for cointegrated variables requires the additional condition that the speed of adjustment coefficient be equal to zero. In this set up, statistical significance of the estimated adjustment parameters η_C and η_E should help qualify further the nature of causality relationship between C and E. Thus, for example, if $H_0 : \beta_{Ei} = 0$ for all $i(i = 1, m)$, η_E =0 is not rejected and at the same time $H_0 : \gamma_{Ci} = 0$ for all $i(i = 1, m)$, η_C =0 is rejected, one should interpret such a result as corresponding to a situation in which the time path of C is autonomously determined and that of E being caused by C. Other possible results may be interpreted in a similar manner (see Glasure and Lee (1997) and also Asafu-Adjaye (2000) for details).

3. **Data Description and Results**

As mentioned at the outset, for the present exercise we have used cross-country panel data on *PCGDP* (measured in terms of PPP in 1985 US dollar) compiled by Summers and Heston (viz., the RGDPCH series of Penn World Table (Mark 5.6)). Corresponding panel data set on *PCCO2* (measured in metric tons) was obtained from the web site of Carbon Dioxide Analysis Information Center (CDAIC), Oak Ridge National Laboratory of the U. S. A. Combining these two data sets, we compiled a bivariate panel data set of annual observations on income and emission covering 88 countries and the time period from 1960 to 1990 (for a detailed data description, see Coondoo and Dinda (2002)). For

[7] For the specific null hypotheses that are tested to detect the nature of causality in the *ECM* set up, see Section A.3 of the Appendix.

the purpose of the exercise, we grouped the countries into 12 country groups. Table 1 shows the composition of these country groups. The empirical exercise has been done separately for each of these country groups based on the bivariate panel data sets for the individual country groups[8].

Table 2 presents the country-group-specific results of unit root test for logarithm of *PCGDP* and logarithm of *PCCO2* (i.e., income and emission respectively, in our terminology) based on the *IPS* method. In each case the test was done twice – viz., once assuming presence of a deterministic time trend in the data generating process and again without making such an assumption. The results show that at 5 per cent level of significance the null hypothesis of unit root cannot be rejected in any of the cases, except for income for Eastern Europe when presence of a deterministic time trend in the data generating process is not assumed[9]. One may thus conclude that the country group-specific time series of both the variables under consideration are by and large non-stationary. A repetition of the same test on the first-differenced data set showed rejection of the null hypothesis of unit root in all the cases. It thus indicates that the country-specific time series of both income and emission were integrated of order 1(i.e., they were *I(1)*, symbolically).

In the next step, we examined whether or not for individual country groups the null hypothesis that income and emission were *not cointegrated* might be rejected. As

[8] It may be pointed out here that the states/regions covered by the erstwhile U S S R have been left out from this exercise as past data for these states/regions are not available. It should be noted that countries falling into the same group are more or less in a similar state of economic development.

[9] In this case the test turned out to be marginally significant at the 5 per cent level in the *without time trend* case and was non-significant in the *with time trend* case. Such a result may be possible only if an increasing (decreasing) deterministic time trend gets canceled with a decreasing (increasing) stochastic time trend.

explained in the Appendix, the bivariate *Engle-Granger* methodology of cointegration[10] and the *IPS* unit root test procedure was used for this examination. The results of this test are presented in Table 3. Following the *Engle-Granger* convention, for each country group we tested cointegration twice, viz., once treating income as the dependent variable and emission as the independent variable and again interchanging the dependent-independent status of these two variables. The entries under the column heading income (emission) are the computed *IPS* *t*-statistic values for the *cointegration unit root test* when income (emission) was taken as the dependent variable. Here also in each case the cointegration test[11] was done twice – viz., once assuming presence of a deterministic time trend in the residuals of the cointegrating regression equation and again without making such an assumption. In Table 3 country group-specific values of these four test statistics are presented.

Table 3 may be summarized as follows: The results of cointegration appear to be sensitive to whether or not presence of deterministic time trend in the e_{it}'s (i.e., the regression residuals defined in relation (A3) of the Appendix) is assumed. When e_{it}'s were assumed not to contain any deterministic time trend, in most of the cases the result of cointegration was observed to depend upon whether income or emission was taken as the dependent variable. Exceptions were Central America, America as a whole and Eastern Europe. In all these cases the hypothesis of cointegration was not rejected irrespective of whether income or emission was used as the dependent variable. On the other hand, when presence of deterministic time trend in e_{it}'s was assumed, the

[10] In Engle and Granger's (1987) original definition, cointregation refers to a linear relationship between non-stationary variables. Holtz Eakin and selden (1995) show the evidence suggesting a linear relationship between per capita income and CO_2 emission. We also observe the monotonic relationship between income and emission.

[11] That is, the unit root test of the residuals of the estimated long run relationship between y_{it} and x_{it}.

cointegration results obtained by treating income as the dependent variable mostly agreed with the corresponding results obtained by treating emission as the dependent variable[12]. Thus in this case irrespective of whether emission or income was taken as the dependent variable, the null hypothesis of cointegration was not rejected (equivalently, the null hypothesis of unit root of e_{it}'s was rejected) for Africa, Western Europe, Europe and the World. In other words, for these country groups time series of income and emission seemed to obey a long run equilibrium relationship. For North America, South America, Asia, Asia excluding Japan and Oceania, on the other hand, the null hypothesis of cointegration was rejected (i.e., the null hypothesis of unit root of e_{it}'s was not rejected). For the remaining country groups (viz., Central America, America and Eastern Europe) the null hypothesis of cointegration was not rejected when emission had been taken as the dependent variable, but it was rejected when income had been taken as the dependent variable.

Next, using the country group-specific panel data, we estimated the alternative versions of the *ECM* - viz., equation (A5) and (A6) of the Appendix, which we referred to as models I and II, respectively. This estimation was done only for those country groups for which the null hypothesis of cointegration was not rejected (viz., Africa, Central America, America as a whole, Eastern Europe, Western Europe, Europe as a whole and the World). In each case the *ECM* was estimated using three different econometric specifications of the panel data regression equation – viz., ordinary least squares (OLS),

[12] It is well known that in case of the Engle-Granger methodology the result of the cointegration test may be sensitive to the choice of the dependent variable of the cointegration regression in case of *not large enough* samples. The power of the unit root test, on the other hand, may also depend on whether or not a deterministic trend is present in the data generating process and has been incorporated in the regression model used to test unit root. Sometimes it is suggested that when the regression model estimated for testing unit root contains a deterministic trend component and the test rejects the null hypothesis of presence of a unit root, that is a sufficient indication of absence of an unit root (see, Enders (1995) pp. 254-258).

fixed effects (FE) model and random effects (RE) model[13]. In our exercise the FE model turned out to be the appropriate choice for almost all the country groups. The country group-specific estimates of the regression coefficients of the two versions of the *fixed effects ECM* (viz., models I and II) are presented in Table 4.

It may be noted that the estimated adjustment parameters (i.e., the coefficient of the *EC term*) in Table 4 are all statistically significant with the *expected* negative sign (in all cases except for Western Europe when emission is taken as the dependent variable). Since in all these cases income and emission are cointegrated, such a result is only to be expected. This is because of the following reason: as the pair of variables is cointegrated, over a long period of time they tend to move in unison. This means that if moves over time always trying to be on the *long run equilibrium* relationship.

As is well known, the *ECM* tries to explain the observed short run variations of the dependable variable in terms of variations of the lagged value of the dependent variable and the other explanatory variable of the model. Following the explanation given in Section 2 and the Appendix, the nature of *Granger causality* between the variables under study underlying the given data set may be examined by testing null hypotheses specifying relevant parametric restrictions on the estimated *ECM* (See Table 6a).

4. **Interpretation of Results**

In Table 4 the country group/continent-specific FE estimates of the pair of *ECM* equations (i.e., equations (A5) and (A6) of Appendix) based on panel data have been

[13] OLS is known to be generally inefficient for panel data regression estimation. Choice between FE and RE depends upon whether or not the null hypothesis $H_0 : \alpha_i = \alpha$ for $i = 1,2,..., N$, is rejected, where α_i denotes the intercept for the *ith* unit. FE is chosen if H_0 is not rejected.

reproduced. We shall now attempt to explain the results of Table 4 from the point of view of causality[14] due to short run fluctuations along with long run equilibrium relationship. As is well known, the Error Correction Model (*ECM*) depicts the short-run dynamics of the variables of a system when their variables deviate from equilibrium relation(s) governing their long run movements.

The dependent variables of equation (A5) and (A6) of Appendix are r_t and r_t^* measuring growth rate[15] of income and emission, respectively. So, in general, we may write equation (A5) as $r_t = \sum_{i=1}^{T_{11}} \alpha_{1i} r_{t-i} + \sum_{j=1}^{T_{12}} \beta_{1j} r_{t-j}^* + \eta_y EC_{t-1} + u_{1t}$ and equation (A6) as $r_t^* = \sum_{i=1}^{T_{21}} \alpha_{2i} r_{t-i} + \sum_{j=1}^{T_{22}} \beta_{2j} r_{t-j}^* + \eta_x EC_{t-1} + u_{2t}$, where *EC* is error correction term, u_{1t} and u_{2t} are white noise error terms with zero expectations. As we have already, seen, the estimated coefficient of the *EC term* in Table 4 are all statistically significant with an *expected negative* sign (in all cases except for Western Europe, in which significant (viz., at 10%) level is low, when emission is taken as the dependent variable). Now, for a specific country group these equations take specific form depending on the statistical significance of the individual parameters of the above pair of equations. We discuss these cases below and also examine their implications for short run movement from the point of view of causality.

Consider first the case of Africa for which not all the estimated parameters are significant. Thus, we have $r_t = \alpha_1 r_{t-1} + \alpha_2 r_{t-2} - \eta_y EC_{t-1} + u_{1t}$, $\alpha_1, \alpha_2, \eta_y > 0$ and

[14] It should be noted that in our earlier study, (See Coondoo and Dinda 2002) in which, we find the causal relationship between income and emission using Granger Causality Technique which remain same in this study in short run but differ in long run.

[15] $\Delta Y_t = \Delta \log(PCGDP) = r_t$ and $\Delta X_t = \Delta \log(PCCO2) = r_t^*$.

$r_t^* = -\beta_1 r_{t-1}^* - \beta_3 r_{t-3}^* - \eta_x EC_{t-1} + u_{2t}$; $\beta_1, \beta_3, \eta_x > 0$. Thus, r_t and r_t^* follow auto-regressive processes and are autonomous in short run, although a statistically significant long run relationship exists between them.

For Central America and America as a whole, we have $r_t = \alpha_1 r_{t-1} - \eta_y EC_{t-1} + u_{1t}$ and $r_t^* = \alpha_1 r_{t-1} - \beta_1 r_{t-1}^* - \beta_2 r_{t-2}^* - \eta_x EC_{t-1} + u_{2t}$; $\alpha_1,\ \beta_1, \beta_2, \eta_x > 0$. Here, r_t, following a first order auto-regressive process, is clearly autonomous. On the other hand, r_t^* significantly depends upon both r_{t-1} and its own past values. Thus, we have a case of income to emission causality in the short run.

Next, let us consider the cases of Western Europe. We have $r_t = \alpha_1 r_{t-1} - \alpha_2 r_{t-2} + \beta_1 r_{t-1}^* - \beta_2 r_{t-2}^* - \eta_y EC_{t-1} + u_{1t}$ $\alpha_1, \alpha_2,\ \beta_1, \beta_3, \eta_y > 0$ and $r_t^* = -\eta_x EC_{t-1} + u_{2t}$ (coefficient of EC term is significant at 10% level). These results suggest that the rate of growth of emission has reached a stage of *stationarity* maintaining a long run equilibrium relationship with the rate of growth of income, but in short run r_t significantly depends on both its own past value and r_{t-1}^*. This implies that any shock in r_{t-1}^* will cause a corresponding shock in r_t. Hence, we have a very specific kind of emission to income *reverse* causality for Western Europe.

Finally, we have $r_t = \alpha_1 r_{t-1} + \alpha_2 r_{t-3} - \beta_2 r_{t-2}^* - \eta_y EC_{t-1} + u_{1t}$ $\alpha_1, \alpha_2, \beta_2, \eta_y > 0$ for Eastern Europe and $r_t = \alpha_1 r_{t-1} - \alpha_2 r_{t-2} + \beta_1 r_{t-1}^* - \beta_2 r_{t-2}^* - \eta_y EC_{t-1} + u_{1t}$; $\alpha_1, \alpha_2, \beta_1, \beta_2, \eta_y > 0$ for Europe as a whole; and $r_t^* = -\eta_x EC_{t-1} + u_{2t}$ for both. Thus, here the growth rate of emission is stationary with a long run equilibrium relationship. Growth rate of income, being dependent on the growth rate of emission, is also stationary but any shock in emission growth rate r_t^* would cause a fluctuation in the income growth rate. Hence, in this case also there is reverse causality from emission to income. However, in these cases the emission to income causality is supplemented by an additional autoregressive effect of income growth. This means that a sudden drop in the emission rate will cause not only a corresponding immediate negative shock in the income growth rate, the effect will linger due to the significant autoregressive element that governs the income growth rate.

Now, let us see the long run income-emission relationship (as given by the estimated cointegrating vector, viz., (1, $-b_0$, $-b_1$)) and also the speed of adjustment (η) for different country groups. As is well known, the cointegrating vectors of different groups give long run relationship between income and emission for individual country groups. The cointegrating vectors[16] for Africa, Central America, America as a whole, Eastern Europe, Western Europe, Europe as a whole and the World as a whole are presented in Table5. The parameters η_y and η_x in Table 6b are interpreted as the speed of adjustment coefficients which measure the speed at which the values of y_t and x_t come back to long run equilibrium levels, once they deviate from the long run equilibrium relationship. These parameters are of particular interest in that they have important implications for the dynamics of the system. As indicated above, the adjustment coefficients (i.e., the coefficient associated with the *EC* term) show that if any deviation from the long run equilibrium occurs in one period, how much error is corrected by that variable in the next period. The negative sign of the estimated speed of adjustment coefficients are in accord

[16] A pair of co-integrating vectors has been reported in Table 5 for individual country group by changing the status of dependent and independent variables. Standard normalization process slightly differs in these cases because of the presence of country effects or some other fluctuations, although both the variable are cointegrated for individual country groups.

with convergence toward long run equilibrium. The larger the value of η, stronger is the response of the variable to the previous period's deviation from long run equilibrium, if any. Here we have found that η is large for Africa (26.3%) and Central America (18.6%) and is small for Western Europe (2.8%). This implies that in the case of Western Europe any deviation from long run equilibrium of the value of y_t and x_t requires much longer time to restore equilibrium. Since all the η's are statistically significant for all country groups in both the models, any change in one variable is expected to affect the other variable through a feedback system. This implies more or less a bi-directional causal relationship between income and emission for all the country groups. It should be noted that if we ignore the *EC* term, the results of Granger causality in our earlier study (See, Coondoo and Dinda 2002) remain same in this case also. Considering the *EC* term, which is statistically significant and interpreted as a source of causality in the long run sense, the ECM results differ from that of our earlier results. In *ECM*, we find both long run relations with short run fluctuations. So, the results of *ECM* are qualitatively different from that of Granger causality.

For a comprehensive study, we should address the issue of cross sectional dependence. For example CO_2 must be easily transmitted from one country to the other through trade. We assume that the openness of an economy can provide the evidence of cross sectional dependence. Degree of openness of an economy may also influence the nature of income-emission causality. To be specific, a highly open economy, because of its easy access to fuel through international trade, may not face the fuel supply constraint and hence continue to have the income to emission causality problem.

The openness measure is defined as a ratio of (export+import) to GDP at current international prices. The measure of openness is given in the Penn World Table for individual country for each year. Using this data we examine the income-emission relation for all the country -groups. Our empirical findings suggest that openness[17] reduce CO_2 emission in Western Europe and Europe as a whole, where as it increases emission in Africa, Central America (See, Hettige et al. 1992). So, there is a clear evidence that developed countries import the pollution -intensive products which are exported by developing or under developed countries (See also, Agras and Chapman 1999).

5. **Conclusion**

The basic objective of this study was to examine the nature of causality between income and CO_2 emission using a cross-country panel data set. This paper presents the results of investigation of the causality issue based on time series econometric techniques of unit root test, co-integration and related error correction model estimation. Using country-group specific panel data on income and emission, we have found that for seven country groups (viz., Africa, Central America, America as a whole, Eastern Europe, Western Europe, Europe as a whole and World as a whole) income and emission are cointegrated. Thus, for these country groups over a long period of time income and emission tend to move in unison. Examination of causality based on estimated Engle-Granger error correction model gives pattern of causality which are some time quite different from those given by the standard Granger Causality Test. Here we find that bi-directional causality between income and emissions exist for more or less all the country groups.

[17] Hettige et al. (1992) find that toxic intensity decreases with openness of the economy, but the growth rate of the toxic intensity of manufacturing increased in the poorest countries.

Thus, any change in one variable is expected to affect the other variable through a feedback system.

Let us enumerate the limitations of the present study. A comprehensive analysis of income-emission relationship would necessarily call for an examination of the effects of such determinants as the type of fuel used, the sectoral composition of income/GDP, available technology and the price of fuel, among other things. We hope to undertake a follow up study looking into this aspect of the problem. Further, any meaningful policy discussion for control of global emission should require a careful examination of the cross-country distributional patterns of global income and corresponding aggregate emission and their changes over time, keeping in mind the nature of causality that is operative in individual cases. Such a study should be next on our research agenda.

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Appendix
Econometric Methods used

As already mentioned, in this exercise we have examined whether income-emission data for different country groups were cointegrated using the Engle-Granger bivariate cointegration analysis framework and estimated *ECM* for country groups for which cointegration was observed to be significant, using econometric techniques appropriate for a panel data set[18]. The econometric exercise involved three steps. In the first step, the unit roots test was performed to ascertain whether or not the time series of the variables (i.e., natural logarithm of *PCGDP* and *PCCO2*, henceforth denoted by y_t and x_t, respectively) contained stochastic trend. In the second step, cointegration of income and emission was examined. Finally, in the third step, the *ECM* was estimated for those country groups for which cointegration of income and emission had been found.

In the first step the *IPS* panel data unit root test procedure was used to test presence of unit root in the time series data sets for individual country groups. The same procedure was also used in the second step while performing the Engle-Granger bivariate cointegration analysis. Finally, the *ECM* in the third step was estimated by using panel data regression technique. In what follows, we describe briefly the econometric procedures that we have used in the three steps of the present exercise.

A.1 IPS Unit Root Test

For a balanced panel data set $\left(y_{it}, i = 1,2,...,N; t = 1,2,...,T\right)$, where i and t denote cross-sectional unit and time, respectively; Im *et al*. considered the following linear regression set up for developing their panel unit root test

[18] As is well known, the *ECM* is a comprehensive linear regression equation specification which provides a description of the possible nature of interdependence of the short run movements of a pair of co-integrated variable keeping in view the fact that they bear a long run equilibrium relationship.

$$y_{it} = \rho_i y_{it-1} + \sum_{j=1}^{p} \theta_j \Delta y_{it-j} + z'_{it}\gamma + \varepsilon_{it} \ . \qquad \text{(A1)}$$

Here $z'_{it}\gamma$ denotes the deterministic component of y_{it} which may be zero, a common constant intercept, a time-invariant fixed effect μ_i or a fixed effect that varies both across *i* and over *t* and ε_{it}'s are white noise equation disturbance terms. Note that in (A1) the autoregressive parameter ρ_i is allowed to vary across units[19]. The null hypothesis for the *IPS* unit root test is H_0: $\rho_i = 1$ for all *i* and the corresponding alternative hypothesis is H_1: $\rho_i < 1$ for at least one *i*. As ρ_i is allowed to vary across *i*, the *IPS* test procedure is based on the average of the unit-specific unit root test statistics. Specifically, this test uses the average of the unit-specific *Augmented Dickey Fuller (ADF)* test statistics, which has been called the *t-bar* statistic. This is as given below:

$$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{\rho_i} \ ,$$

t_{ρ_i} being the t-statistic for testing $H_0: \ \rho_i = 1$ in (1). It is shown that, given *N*, as $T \rightarrow \infty$, t_{ρ_i} weakly converges to $t_{iT} = \dfrac{\int_0^1 W_{iz} dW_{iz}}{\sqrt{\int_0^1 W_{iz}^2}}$, where W_{iz} denotes a Brownian motion[20].

Assuming t_{iT}'s to be independent and identically distributed with finite mean and variance, the *IPS* test statistic is derived as

12 Quah (1994) considered equation (A1) without the second and third terms as the model for his panel unit root test. Levin and Lin (1993) considered a more general model to allow for fixed effects, individual deterministic trends and heterogeneous serially correlated errors. In fact, they considered equation (A1) without the second term as their model specification. They, however, assumed the units to be *iid* $(0, \sigma_\varepsilon^{\ 2})$ and also $\rho_i = \rho$ for all i. Here H_0: $\rho = 1$ against H_1: $\rho < 1$. Levin and Lin's test is thus restrictive as it requires ρ_i to be the same for all i.

[20] Brownian motion is also called *Wiener Process* (see, Hamilton (1994), ch-17, p-478).

$$t_{IPS} = \frac{\sqrt{N}(\bar{t} - E(t_{iT}; H_0 : \rho_i = 1)}{\sqrt{\operatorname{var}(t_{iT}; H_0 : \rho_i = 1)}}. \tag{A2}$$

So far as the actual test procedure is concerned, *IPS* provide table of estimates of $E(t_{iT}; H_0 : \rho_i = 1 \forall i)$ and corresponding $\operatorname{var}(t_{iT}; H_0 : \rho_i = 1 \forall i)$ for different values of T and p computed by stochastic simulation for two versions of the *ADF(p)* regression–viz., $\Delta y_t = \alpha + \beta y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + error$ for the *without time trend case* and $\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + error$ for the *with time trend case*. Given these and the computed value of $\bar{t}$ for the given panel data, t_{IPS} is calculated using (A2). The table of corresponding critical values for the given values of N and T and various levels of significance are provided in Im et al (1997).

A.2 Co-integration Test for Panel data

Given a set of panel data on *(K+1)* variables $y, x_j, j = 1, K$, the single equation *IPS* cointegration test proceeds as follows: First, the linear regression equation $y_{it} = \sum_{j=1}^{K} \beta_{ji} x_{jit} + error$ is estimated separately for $i = 1, 2, \ldots, N$ individual units and the regression residuals

$$e_{it} = y_{it} - \sum_{j=1}^{K} \hat{\beta}_{ji} x_{jit} \text{ , } i = 1,2,\ldots,N; t = 1,2,\ldots,T \tag{A3}$$

are obtained, where $\hat{\beta}_{ji}$'s denote the estimated parameters of the regression equation for the *ith* unit. These estimated linear regression equations may be taken as estimate of the long run equilibrium relationship between y and the x's, in case the variables turn out to be cointegrated[21]. Next, for each i the following *ADF(p)* equation is estimated:

$$e_{it} = \lambda e_{it-1} + \sum_{j=1}^{p} \theta_{ij} \Delta e_{it-j} + z'_{it}\gamma + v_{itp} \qquad \text{(A4)}$$

where $z'_{it}\gamma$ is same as defined for equation (1) above and v_{itp} is the equation disturbance term assumed to be a white noise. Here also one may consider two alternative specifications of equation (A4) - viz., one without a time trend and another with a time trend. The *IPS* methodology of cointegration[22] test for the set of variables under consideration thus involves the test of unit root for the regression residuals $\{e_{it}\}$- i.e., the null hypothesis H_0: $\lambda = 1$ (i.e., no cointegration) is tested against the alternative hypothesis H_1: $\lambda < 1$ (i.e., cointegration). In our empirical exercise, we have performed the cointegration test twice, viz., once treating logarithm of *PCGDP* (i.e., y) as the dependent variable and logarithm of *PCCO2* (i.e., x) as the independent variable and again reversing the status of these variables.

A.3 Estimation of ECM from Panel data

Once the pair of variables (x, y) has been found to be cointegrated, the next step in the Engle – Granger methodology is to model the short run variations of the variables. This is done by estimating the *ECM*. For a bivariate case as the present one, the *ECM,* which is implied by the well known *Granger Representation Theorem* (see Hamilton (1994), Ch.19, pp. 581-582), is expressed as either of the following linear regression equations:

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[21] It may be noted that when the variables are cointegrated, the true relationship underlying this linear regression equation is a long run equilibrium relationship between y and the x's. Kao, Chiang and Chen (1999) pointed out that for a set of cointegrated variables the use of *OLS* to estimate this long run equilibrium relationship from the given set of panel data will give biased results in a finite sample and recommended the use of Dynamic *OLS (DOLS)* for minimisation of such bias. See Kao and Chiang (1998) for the definition of *DOLS*.

[22] Panel data cointegration test is also performed by Kao (1999), McCoskey and Kao (1998).

$$\Delta y_{it} = \mu_{yx} + \sum_{j=1}^{T_{11}} \alpha_{1j} \Delta y_{it-j} + \sum_{j=1}^{T_{12}} \beta_{1j} \Delta x_{it-j} + \eta_{yx} ECY_{it-1} + u_{1it} \qquad \text{(A5)}$$

$$\Delta x_{it} = \mu_{xy} + \sum_{j=1}^{T_{21}} \beta_{2j} \Delta x_{it-j} + \sum_{j=1}^{T_{22}} \alpha_{2j} \Delta y_{it-j} + \eta_{xy} ECX_{it-1} + u_{2it} \,. \qquad \text{(A6)}$$

Here Δ denotes the difference operator; $T_{lm}, l, m = 1,2$ denotes the number of lagged values of Δy_i and Δx_i that affect the current value of these *differenced* variables; μ, α, β and η denote regression parameters; $u_{lit}, l = 1,2$ are the equation disturbance terms (that should be white noises when the *ECM* has been adequately specified); and finally, $ECY_{it} = y_{it} - \hat{\phi}_0 - \hat{\phi}_1 x_{it}$ and $ECX_{it} = x_{it} - \hat{\varphi}_0 - \hat{\varphi}_1 y_{it}$ are the error correction terms (hereafter refereed to as *EC terms*) measuring deviation of $y_{it}(x_{it})$ from the corresponding long run equilibrium value, given $x_{it}(y_{it})$.[23] The parameters η_{yx} and η_{xy} in equations (A5) and (A6) are called the adjustment parameters. They are expected to have negative values[24]. In this set up the nature of Granger causality is determined as follows:

(1) if $\beta_{1j} = 0$ for all *j* and $\eta_{yx} = 0$, *x* may be said not to *Granger cause y*;

(2) if $\alpha_{2j} = 0$ for all *j* and $\eta_{xy} = 0$, *y* may be said not to *Granger cause x*;

(3) if (1) holds but (2) does not, *Granger causality* may be said to be *unidirectional from y to x*;

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[23] Note that here $y_{it} = \phi_0 + \phi_1 x_{it} + \varepsilon_{1it}$ and $x_{it} = \varphi_0 + \varphi_1 y_{it} + \varepsilon_{2it}$ are alternative representations of the (population) long run *equilibrium* relationship between *y* and *x*, where ε's are the stationary error terms. As y and *x* are cointegrated, by the definition of cointegration for some constants, $\omega_0 + \omega_1 y_{it} + \omega_2 x_{it} = \varepsilon_{it}$, where ε_{it} is a stationary error term and $\omega = (\omega_0, \omega_1, \omega_2)$ is the non- normalized cointegrating vector. Thus, by normalizing ω one may write the long run equilibrium relationship for *(y,x)* in either form as shown above.

[24] This is for the following reason. If, for example, $ECY_{it-1} > 0$ for some *i,t,* it means that the realized value of y_i exceeded the corresponding long run equilibrium level at *t-1*, given x_{it}. Now since y_i and x_i are cointegrated, once a positive deviation from the long run equilibrium level takes place, the actual value must try to move in the opposite direction in subsequent time points in an attempt to restore the long run equilibrium and hence the negative sign of η_{yx} and η_{xy}.

(4) Conversely, if (1) does not hold but (2) does, *Granger causality* may be said to be *unidirectional*
from x to y;
(5) if both (1) and (2) do not hold, *Granger causality* between *x* and *y* may be said to be *bi-directional*; and finally
(6) if both (1) and (2) hold, *Granger causality* between *x* and *y* may be said to be absent (see Enders (1995), Glasure and Lee (1997) and Asafu-Adjaye (2000) for details).

In the present exercise, equations (A5) and (A6) (henceforth referred to as model I and model II, respectively) were estimated separately for each country group, using the panel data set for the country group. Country group-specific inference about the nature of *Granger causality* between *x* and *y* were then drawn by performing appropriate test of hypothesis for the relevant parameters of model I and II, as laid down above. For example, to test the null hypothesis that *x* does not *Granger cause y,* one should perform an F-test for the null hypothesis $H_0 : \beta_{1j} = 0, j = 1,2,...,T_{12}, \ \eta_{yx} = 0$, using model I. Similarly, to test the null hypothesis that *y* does not *Granger cause x*, an F-test for the null hypothesis $H_0 : \alpha_{2j} = 0, j = 1,2,...,T_{22}, \eta_{xy} = 0$ using model II will be required. Given the results of these two basic F-tests, the remaining null hypotheses (3)- (6) laid down above can be tested.

Table 1. Continent-wise list of country groups and countries covered

Continent	Country Group	Countries Covered
Africa	Africa	Algeria, Cameroon, Cape Verde Island, Central African Republic, Comoros, Congo, Egypt, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Madagascar, Mali, Mauritania, Mauritius, Morocco, Mozambique, Nigeria, Senegal, South Africa, Togo, Tunisia, Uganda, Zimbabwe.
America	North America	Canada and USA
	Central America	Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Trinidad & Tobago.
	South America	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela.
Asia	Japan	Japan.
	Asia (excluding Japan)	China, Hong Kong, India, Indonesia, Iran, Israel, Jordan, Korea Republic, Philippines, Singapore, Sri Lank, Syria, Thailand.
Europe	East Europe	Austria, Czechoslovakia, Finland, Greece, Turkey, Yugoslavia.
	Western Europe	Belgium, Cyprus, Denmark, France, West Germany, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, U.K.
Oceania	Oceania	Australia, Fiji, New Zealand, Papua Guinea.

Table 2. Results of Panel Unit Root Test : IPS $\bar{t}$ statistic by Country Group

Country Group	With t-bar income	Time For emission	Trend Critical Value (5% level)	Without t-bar income	Time For emission	Trend Critical Value (5% level)
Africa	-0.289	-0.376	-2.45	2.469	0.664	-1.82
North America	-0.330	0.486	-2.94	0.296	-1.384	-2.30
Central America	2.109	1.025	-2.60	-0.038	-0.302	-1.99
South America	1.912	0.980	-2.60	1.210	0.949	-1.99
America	2.611	1.498	-2.47	0.880	0.019	-1.84
Japan	NA	NA		NA	NA	
Asia(excl. Japan)	-0.734	-0.250	-2.56	6.068	2.351	-1.94
Asia	-0.842	-0.307	-2.54	5.757	2.075	-1.92
East Europe	3.238	1.308	-2.74	-0.592	-2.123	-2.12
West Europe	-0.701	-0.605	-2.52	3.283	0.022	-1.89
Europe	1.093	0.167	-2.47	2.491	-1.090	-1.84
Oceania	-0.250	-0.488	-2.84	0.949	0.293	-2.21
World	1.306	0.402	-2.32	5.526	0.715	-1.68

Note: 1. Im *et al* (1997) give Tables of critical values of their Panel unit root test statistic for selected combinations of N and T values. The critical values shown in the present Table have been derived from the original Tables by interpolation whereever required.

2. NA denotes *not available*. For Japan, a single country, the panel unit root test was not applicable. Hence no result is shown against Japan.

Table 3. Results of Cointegration Test : IPS $\bar{t}$ statistic by Country Group

Country Group	without time trend		critical value	with time trend		critical value
	income	emission		income	emission	
Africa	-0.880	-2.571***	-1.82	-2.643***	-4.180***	-2.45
North America	-0.608	-2.182	-2.30	-1.665	-0.567	-2.94
Central America	-2.015*	-2.263***	-1.99	0.905	-2.524*	-2.60
South America	-0.846	-1.091	-1.99	-1.384	-2.123	-2.60
America	-2.112**	-2.919***	-1.84	-0.825	-3.304***	-2.47
Japan	NA	NA		NA	NA	
Asia(excl. Jap)	3.428	-0.054	-1.94	-1.862	-1.543	-2.56
Asia	3.052	-0.398	-1.92	-1.879	-1.513	-2.54
East Europe	-2.089*	-3.523***	-2.12	-2.237	-4.649***	-2.74
West Europe	0.572	-2.484***	-1.89	-3.088***	-3.935***	-2.52
Europe	-0.603	-3.958***	-1.84	-3.802***	-5.784***	-2.47
Oceania	-0.363	-0.978	-2.21	-0.922	-1.520	-2.84
World	-0.696	-5.203***	-1.68	-4.697***	-7.744***	-2.32

Note: "*", "**" and "***" denote the significance level at 10%, 5% and 1%, respectively. Critical values shown correspond to the 5% level of significance. NA denotes "Not Applicable".

Table 4. Estimated parameters of the *ECM* for country groups for which cointegration hypothesis was not rejected

Country group	Model	Estimated coefficient of the explanatory variable (Δ log)						
		income_1	income _2	income_3	emission_1	emission_2	emission_3	EC term
Africa	I (3)	0.10	0.10	-0.07	0.00	-0.00	-0.02	-0.09
		(2.59)	(2.56)	(-1.79)	(0.02)	(-0.25)	(-1.92)	(-4.77)
	II (3)	0.05	0.21	-0.18	-0.20	-0.08	-0.17	-0.26
		(0.31)	(1.31)	(-1.12)	(-4.59)	(-1.72)	(-4.12)	(-7.95)
Central America	I(2)	0.192	0.019	-	0.004	0.016	-	-0.0906
		(2.993)	(0.3)		(0.18)	(0.8)		(-2.62)
	II(2)	0.782	0.152	-	-0.4	-0.281	-	-0.186
		(4.11)	(0.81)		(-5.97)	(-4.7)		(-3.42)
America	I(2)	0.229	-0.02	-	0.012	0.011	-	-0.059
		(5.31)	(-0.45)		(0.7)	(0.68)		(-3.16)
	II(2)	0.666	0.191	-	-0.36	-0.238	-	-0.091
		(6.09)	(1.71)		(-8.14)	(-5.76)		(-3.28)
Eastern Europe	I(3)	0.172	-0.056	0.205	0.052	-0.138	-0.018	-0.083
		(2.18)	(-0.72)	(2.7)	(1.09)	(-2.98)	(-0.37)	(-4.58)
	II(2)	0.029	0.145	-	0.014	-0.018	-	-0.132
		(0.22)	(1.11)		(0.19)	(-0.24)		(-4.85)
Western Europe	I (2)	0.24	-0.18	-	0.04	-0.04	-	-0.03
		(4.85)	(-3.62)		(1.97)	(-2.12)		(-3.33)
	II (2)	0.16	0.08	-	0.05	-0.07	-	-0.03
		(1.12)	(0.59)		(0.98)	(-1.23)		(-1.74)
Europe	I (3)	0.23	-0.13	0.08	0.04	-0.06	-0.02	-0.04
		(5.26)	(-2.92)	(1.81)	(2.32)	(-3.30)	(-0.76)	(-4.89)
	II (2)	0.12	0.11	-	0.07	-0.04	-	-0.07
		(1.10)	(1.06)		(1.52)	(-0.97)		(-4.00)
World	I (3)	0.12	0.03	-0.03	0.02	-0.00	-0.01	-0.04
		(5.45)	(1.55)	(-1.47)	(1.9)	(-0.12)	(-1.66)	(-5.33)
	II (3)	0.26	0.27	-0.02	-0.22	-0.09	-0.12	-0.17
		(3.54)	(3.76)	(-0.32)	(-9.40)	(-4.06)	(-5.44)	(-11.12)

Note: 1. Figure in brackets in the "model" column indicates the optimum number of lagged variables used as regressors in the *ECM* as determined for the given data set.

2. For each country group and model the first row of 3^{rd} to 9^{th} column gives the estimated coefficients. The corresponding figures in brackets in the next row of these columns are the corresponding t-ratios.

Table 5: Country group-specific Estimated Co-integrating relationship.

($y_{it} = b_0 + b_1 x_{it}$ and $x_{it} = b_0' + b_1' y_{it}$)

Country Group	Dependent variable Y		Dependent variable X	
	$-b_0$	$-b_1$	$-b_0'$	$-b_1'$
Africa	-7.88	-0.36	15.076	-1.80
	(.0262)	(.00927)	(.3214)	(.0459)
Central America	-8.39	-0.46	14.13	-1.65
	(.0231)	(.0149)	(.4209)	(.0535)
America	-8.53	-0.54	14.0	-1.63
	(.0112)	(.00779)	(.192)	(.0237)
Eastern Europe	-8.33	-0.36	5.59	-0.697
	(.0393)	(.046)	(.7477)	(.0884)
Western Europe	-8.71	-0.45	8.78	-1.05
	(.0206)	(.0214)	(.4539)	(.0502)
Europe	-8.58	-0.48	7.02	-0.86
	(.0205)	(.022)	(.3483)	(.0392)
World	-8.46	-0.55	12.96	-1.51
	(.00898)	(.00476)	(.1049)	(.0131)

Note: Figures in parentheses are standard errors. All the estimated coefficients are statistically significant.

Table 6a: Computed F values for test of parametric restriction on the *ECM* relating to the *GCT*

Country Group	Model (lag)	OLS regression	FE regression	RE regression
Africa	I(3)	2.11	1.35	1.45
	II(3)	4.70**	1.07	1.37
Central America	I(2)	1.30	0.35	0.86
	II(2)	16.67**	9.07**	13.34**
America	I(2)	1.40	0.36	0.71
	II(2)	29.15**	21.50**	24.82**
Eastern Europe	I(3)	3.33*	3.80*	3.32*
	II(2)	2.52	0.68	1.75
Western Europe	I(2)	5.01**	4.62**	8.22**
	II(2)	1.73	0.96	4.76**
Europe	I(3)	6.15**	6.20**	6.05**
	II(2)	2.99	1.37	1.83
World	I (3)	4.50**	2.82**	3.47**
	II(3)	24.96**	9.53**	15.46**

Notes:
1. Models I and II relate to the *ECM* equations (A5) and (A6) of the Appendix.
2. Figures in parentheses give the order of the ECM regression equation in terms of the maximum order of lag of variables appearing as regressors.
3. For model I and II the computed F value relates to the null hypothesis $\beta_{1j} = 0$ for all j and $\eta_{yx} = 0$ and $\alpha_{2j} = 0$ for all j and $\eta_{xy} = 0$, respectively.
4. F- values marked by * and ** are significant at 5 and 1 per cent level, respectively.

Table 6b: Estimated values of error correction term for different models in panel data.

Country Group	Model	Pooled(OLS)	Fixed Effect	Random Effect
Africa	I	-0.019	-0.087	-0.027
		(-2.27)**	(-4.77)***	(-2.7)***
	II	-0.054	-0.263	-0.125
		(-3.24)***	(-7.95)***	(-5.36)***
Central America	I	-0.012	-0.091	-0.015
		(-0.92)	(-2.62)***	(-1.06)
	II	-0.022	-0.186	-0.033
		(-1.08)	(-3.42)***	(-1.37)
South America	I	-0.031	-0.076	-0.033
		(-1.88)	(-2.68)***	(-1.93)
	II	-0.025	-0.073	-0.032
		(-1.43)	(-2.36)**	(-1.63)
America	I	-0.015	-0.059	-0.016
		(-1.63)	(-3.16)***	(-1.7)
	II	-0.02	-0.091	-0.025
		(-1.51)	(-3.28)***	(-1.71)
East Europe	I	-0.008	-0.083	-0.023
		(-1.44)	(-4.58)***	(-2.45)**
	II	-0.026	-0.132	-0.043
		(-3.48)***	(-4.85)***	(-3.43)***
West Europe	I	-0.002	-0.028	-0.022
		(-0.93)	(-3.33)***	(-3.63)***
	II	-0.027	-0.034	-0.029
		(-2.98)***	(-1.74)*	(-2.57)**
Europe	I	-0.011	-0.042	-0.012
		(-3.05)***	(-4.89)***	(-3.13)***
	II	-0.027	-0.069	-0.03
		(-4.4)***	(-3.99)***	(-4.16)***
World	I	-0.012	-0.038	-0.015
		(-3.71)***	(-5.33)***	(-3.94)***
	II	-0.028	-0.166	-0.056
		(-4.26)***	(-11.12)***	(-6.38)***

Note: Figures in parentheses are t-ratios. Estimated coefficients significant at 1%, 5% and 10% level are marked with `***', ** and `*' , respectively . NA denotes Not Applicable.