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Some Determinants of CO_2 Emissions in Bangladesh

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Abstract *CO_2 emissions, industrial output growth, population growth and Foreign Direct Investment (FDI) inflows in Bangladesh for 1972–2008 are found non-stationary in terms of both Augmented Dickey– Fuller (ADF) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests with different orders of integration. As a result, the Autoregressive Distributed Lag (ARDL) model and Vector Error-Correction Model (VECM) are estimated. There is evidence of a co-integrating (converging long-run equilibrium) relationship between the variables of long-run causal flows from industrial output growth, population growth and FDI to CO_2 emissions. FDI seems to marginally mitigate CO_2 emissions. Furthermore, short-run interactive net positive feedback effects among the variables are also evidenced.*

1. Introduction

Among a multitude of environmental pollutants, carbon dioxide (henceforth, CO_2) emission is a serious problem in developing countries. This increases at an early stage of industrial expansion as a transition from overdependence on agriculture. Such industrial transformation is heavily dependent on energy intensive technologies. They consciously allow foreign pollution intensive firms to migrate from developed countries where environmental standards are comparatively much higher, which results in high regulatory compliance costs of production. The motivation is to entice Foreign Direct Investment (FDI) for job creation to end abject poverty which is an

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outcome of rising income inequality. Moreover, the degree of environmental awareness is very low in developing countries.

Once a developing country's per capita real income approaches a certain level, the country gains resources to invest in costly environment friendly technologies to mitigate the level of CO_2 emission. As a country's economic structure later gradually transforms from manufacturing to the expanding services sector, CO_2 emission continues to abate. Meanwhile, people become increasingly environmentally conscious for health reasons and continue to press the home country government to raise environmental standards. This phenomenon is described by Kuznet's inverted environmental U-curve.

Bangladesh is a poor developing country where the main means of subsistence is still drawn from agriculture, although its percentage share in GDP continues to fall over time. Bangladesh is only 1/5th the size of the state of Texas in the USA, but yet with over 150 million inhabitants it is almost half the population of the USA. This creates necessitates an increased emphasis on industrialization for domestic consumption and exports to earn hard foreign currencies. Bangladesh also endeavors to attract FDI for job creation. At an early stage of industrialization, the above factors are likely to contribute to significant emissions of CO_2. Additionally, the level of environmental awareness is still relatively low in Bangladesh.

The primary objective of this study is to investigate the role of industrial production, FDI and rising population by determining the level of CO_2 emissions in Bangladesh, using the Autoregressive Distributed Lag (ARDL) model for co-integration and long-run causality with short-run interactive feedback effects. The paper is structured as followed: Section 2 briefly reviews the related literature. Section 3 outlines the ARDL empirical methodology. Section 4 details results and Section 5 offers conclusions and remarks.

2. Brief Review of Related Literature

Grossman and Krueger (1991) found that the long-term relationship between economic growth and environment quality was an inverted U-shaped curve. The phenomenon has been labeled as the Environmental Kuznets Curve (EKC) by Panayotou (1993). The EKC hypothesizes that environment quality deteriorates with the increase of per capita income at the early stage of economic growth and gradually improves when the country reaches a certain level of affluence. Since then, extensive empirical studies have been conducted to test the EKC hypothesis. The effect of economic growth on environmental quality is the basis for many disputes.

Most of the empirical studies are based on multi-countries. In fact, the EKC hypothesis is fundamentally taking place on a national level. However, cross-country analysis assumes that all cross-section countries react identically, no matter how different they are in terms of income, geographical conditions, culture and history (Dijkgraaf and Vollegergn, 1998). In recent years, some researchers have begun to use individual countries to test the EKC hypothesis (i.e. Unruh and Moomaw, 1998; De Brueyn, 2000; Lekakis, 2000; Stern and Common, 2001; Cole, 2003). Besides the income factor, environmental quality is also affected by other factors, such as economic structure, international trade, FDI, environmental regulation and so on; although most of the empirical studies merely focused on the income level. A growing world needs more input to expand outputs, which implies that waste and emissions as by-products of economic activities will increase (Grossman and Krueger, 1995). With economic growth, the production structure will change, from clean agrarian economies to polluting industrial economies and further to clean service economies (Arrow et. al., 1995). As Panayotou (1993) points out, when the sectors of an economy shift mainly from agriculture to industry, pollution intensity increases. This is because more and more resources are exploited and the exhaustion rate of resources begins to exceed the regeneration speed of resources. When the industrial structure enhances further, from energy intensive heavy industry to service and technology-intensive industries, pollution decreases as income grows. The upgrading of industrial structure needs the upgrading of technology. Technical progress makes it possible to replace the heavily polluting technologies with cleaner ones. It is the trade-off between scale effect and technology effect that causes that the environment to deteriorate at the first industrial structural change and improves at the second industrial structural change, making the relationship between environment and economic growth look like an inverted-U curve. The downward sloping portion of the environment and economic growth may be facilitated by advanced economies exporting their pollution-intensive production processes to less-developed countries (Suri and Chapman, 1998).

In another vein, international trade and FDI help explain the EKC hypothesis. International trade and FDI have contradictory impacts on the environment. International trade especially exports and inflows of FDI lead to increased use of land and natural resources, as well as encouraging consumption, which will cause more pollution due to more production and/or consumption, while international trade and FDI also have positive effects on the environment by the composition effect and/or technology effect, which are attributed to Displacement Hypothesis and Pollution Haven Hypothesis (Dinda, 2004). To developing countries, FDI might bring improved efficiency and cleaner technology, which offers opportunities to improve the most damaging phases of industrialization (Goldemberg, 1998). Pollution emissions may drop due to trade openness, since the economies gain more environmental awareness under greater competitive pressure. But trade and FDI might facilitate advanced economies to export their pollution-intensive production processes to less-developed countries due to different environmental stringent policies (Suri and Chapman, 1998). This will speed up the pollution level of less-developed countries. As Arrow et al. (1995) and Stern et al. (1996) pointed out, if there was an EKC type relationship, it might be partly or largely a result of the effects of trade on the distribution of polluting industries.

3. Empirical Methodology

To begin with, the nature of the data distribution of each variable is examined by descriptive statistics. To examine the time series property of each variable, the Augmented Dickey–Fuller test (Dickey and Fuller, 1981; Fuller, 1996) and the KPSS (Kwiatkowski et al., 1992) test have been applied, although such pre-testing is optional in the Autoregressive Distributed Lag (ARDL) model.

In the event of non-stationary of variables, the most commonly used procedures for ascertaining the co-integrating relationship include Engle and Granger (1987) residual-based procedure and Johansen and Juselius (1992, 1999) maximum likelihood-based procedure. Both procedures concentrate on cases in which the underlying variables are integrated of order one, which is highly unlikely in the real world. To address the issue of unequal order of integration of non-stationary variables for a long-term equilibrium relationship and causal flows, the ARDL model or the bound testing procedure suggested by Pesaran et al. (2001) has been used in this study. It is applicable irrespective of whether the regressors in the model are purely I (0) and I (1) or mutually integrated. Another advantage of this approach is that the model uses a sufficient number of lags to capture the Data Generating Process (DGP) in a General to Specific (GETS) modelling framework. A dynamic Error Correction Model (ECM) can also be derived from the ARDL procedure through a simple linear transformation. The ECM integrates the short-run dynamics with the long-run equilibrium relationship without losing long-term memory.

The ARDL procedure based on a bound testing approach uses the following unrestricted model as found in the work of Pesaran and Shin (1999) and Pesaran et al. (2001). Assuming a unique long-run relationship among the weakly exogenous independent variables, the following estimating Vector Error-Correction Model (VECM) is specified:

$$\Delta\ln 〖Car〗_{\downarrow}t = \alpha_{\downarrow}0 + \Sigma_{\downarrow}(i = 1)^{\uparrow}p ≣ 〖b_{\downarrow}(\Delta\ln 〖Car〗_{\downarrow}(t - i)) + \sum_{\downarrow}(i = 0)^{\uparrow}p ▒ 〖c_{\downarrow}$$

$$(\Delta\ln 〖Ind〗_{\downarrow}(t - i)) + \Sigma_{\downarrow}(i = 0)^{\uparrow}p ▒$$

Where, Car = carbon dioxide (CO_2) emission, Ind = industrial output, Fdi = foreign direct investment and Pop = population size. All first-differenced variables here are in natural logs. To implement the bound testing procedure, the following steps are outlined:

First, testing for weak exogeneity, the ARDL procedure is implemented through Vector Autoregressive (VAR) pair-wise Granger Causality/Block Exogeneity Wald Tests. Johansen (1988) stated that the weak exogeneity assumption influences the dynamic properties of the model and must be tested in the full system framework.

Second, equation (1) has been estimated by Ordinary Least Squares (OLS) in order to test for the existence of a co-integrating relationship among the variables through conducting F-test for the joint significance of the coefficients of the lagged variables in levels. The null and the accompanying alternative hypotheses for the co-integrating relationship are

Ho: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ for no co-integration
Ha: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ for co-integration

If the calculated F-statistic is above its upper critical value, the null hypothesis of no long-run relationship can be rejected irrespective of the orders of integration for the time series. Conversely, if the calculated F-statistic falls below its lower critical value, the null hypothesis cannot be rejected. If the calculated F-statistic falls between its lower and upper critical values, the inference remains inconclusive.

Third, on the evidence of co-integrating relationship, the following conditional ARDL (p_1, q_1, q_2 and q_3) model is estimated:

$$\Delta\ln Car_t = \alpha_0 + \sum_{i=1}^{p^1} \alpha_{1\ln Car_{t-i}} + \sum_{i=0}^{q^1} \alpha_{2\ln Ind_{t-i}} + \sum_{i=0}^{q^2} \alpha_{3fdi_{t-i}} + \sum_{i=0}^{q^3} \alpha_4 \ln Pop_{t-i} + \omega_t \ldots\ldots\ldots\ldots\ldots (2)$$

The optimum lag orders in the above are selected by the Akaike Information Criterion (AIC) as found in the work of Akaike (1969). The optimum lags are selected appropriately to reduce residual serial correlation and to avoid over-parameterization. According to the recommendation of Pesaran and Shin (1999) for annual data, a maximum of two lags was selected.

For subsequent use in the VECM, the error-correction term (ECM_{t-1}) is obtained from the following equation:

$$ECM_{t-1} = \ln Car_t - \widehat{\alpha_0} + \sum_{i=1}^{p^1} \widehat{\alpha_1} \ln Car_{t-i} + \sum_{i=0}^{q^1} \widehat{\alpha_2} \ln Ind_{t-i} \sum_{i=0}^{q^2} \widehat{\alpha_3} \ln fdi_{t-i} + \sum_{i=0}^{q^4} \widehat{\alpha_4} \ln Pop_{t-i} \cdots\cdots\cdots \text{(3)}$$

Finally, the short-run and long-run dynamics are captured by estimating the following VECM:

$$\Delta \ln Car_t = \beta_0 + \sum_{i=1}^{p} \beta_{1\,\Delta \ln car_{t-i}} + \sum_{i=0}^{p} \beta_{2\,\Delta \ln ind_{t-i}} + \sum_{i=0}^{p} \beta_{3\,\Delta \ln fdi_{t-i}} + \psi ECM_{t-1} \cdots\cdots\cdots \text{(4)}$$

Where, β are the coefficients relating to the short-run dynamic elasticises and Ψ is the speed of adjustment to the long-run equilibrium associated with the error-correction term, ECM_{t-1}. The expected sign of Ψ is negative. Its statistical significance is reflected through the associated t-value and its numerical magnitude indicates the speed of adjustment towards a long-run equilibrium.

Annual data from 1972 to 2008 are employed in this study. The number of sample observations is relatively small for a meaningful co-integration analysis. A bigger sample period can partially overcome this problem (Hakkio and Rush, 1991). In contrast, when a sample period is relatively small, high frequency data may partially compensate for this deficiency (Zhou, 2001). The CO_2 emission data were obtained from the Carbon Dioxide Information Analysis Center at the Oak Ridge National Laboratory (2009) and are in per capita terms and in metric tons, excluding emissions from land use and agriculture. Industrial production data, obtained from World Development Indicators (2009), were at a constant 2000 (US dollar). FDI data were nominal and in US dollar, obtained also from World Development Indicators (2009) of the World Bank. Population data were obtained from various sources of International Financial Statistics, IMF.

4. Results

The data descriptors are reported in Table 1:

A cursory inspection of Table 1 reveals that all descriptive statistics including Jarque–Bera corroborate normal distribution of each variable except for lnFDI. Weak exogeneity test results are reported in Table 2.

Considering population (lnPop) as exogenous to the system and treating LnIND and LnFDI as weakly exogenous, the parameter of the conditional scalar variable (LnCar) is meaningfully estimated independently of the marginal distribution of LnIND and LnFDI, as stated by Johansen (1988) and Pesaran et al. (2001). The Chi-square value from the underlying VAR model is 36.85419 with p-value

Table 1: Descriptive statistics

Descriptors	LnCAR	LnIND	lnFDI	LnPOP
Mean	–2.055147	22.0682	197.8619	4.696007
Median	–2.009915	21.99266	7	4.698296
Maximum	–1.241329	23.25308	1086.3	5.075174
Minimum	–2.995732	20.53408	–8.000000	4.282068
Std. Dev.	0.512581	0.668197	300.1324	0.238232
Skewness	–0.044043	–0.02596	1.361373	0.006122
Kurtosis	1.780291	2.225368	3.776772	1.844811
Jarque-Bera	2.305483	0.92924	12.3591	2.057524
Probability	0.31577	0.628374	0.002071	0.357449
Sum	–76.04045	816.5233	7320.889	173.7523
Sum Sq. Dev.	9.458613	16.07352	3242861	2.043155
Observations	37	37	37	37

0.0000. This indicates that all level variables are globally exogenous. The individual Chi-square values also support this finding.

Table 2: Weak Exogeneity Tests (VAR pair-wise Granger causality/block exogeneity Wald tests)

Dependent variable: LNCARBON			
Excluded	Chi-sq	Df	Prob.
LNIND	28.36388	3	0
LNFDI	34.33534	3	0
All	36.85419	6	0

The time series property of each variable is examined by both, the ADF test and its counterpart KPSS test. The results are reported in Table 3.

Table 3: Unit Root Tests (ADF and KPSS)

Variables	ADF		KPSS	
Level	1st Difference	Level	1st Difference	Level
lnCAR	–0.694050	–5.970553*	0.732201*	
lnIND	1.810694	–2.429028	0.745831	0.184255*
lnFDI	0.248215	–6.241580*	0.611091*	
lnPop	–1.075871	–6.127511*	0.729319*	

Notes: *The MacKinnon (1996) ADF critical values are –3.752946 and –2.998064 at 1% and 5% levels of significance, respectively. The KPSS (Kwiatkowski et al., 1992) critical values are 0.73900 and 0.46300 at the aforementioned levels of significance, respectively.Table 3 reveals non-stationary of each variable with different orders of integration. Subsequently, the estimates of equation (1) for co-integration are reported in Table 4.

Table 4: F-statistics for Co-integration Relationship

Dep. Var.	F-Statistics	Probability	Out come
FCAR (CAR|IND, FDI,POP)	4.640954	0.001	Co-integration
F IND (IND|CAR, FDI,POP)	3.72323	0.004	No co-integration
F FDI (FDI|CAR, IND,POP)	2.08841	0.067	No co-integration
F POP (POP|CAR, IND,POP)	1.26949	0.306	No co-integration

The asymptotic critical Value bounds are min F =2.86 & Max F =4.01 at 5 % level (Table C1 iii. unrestricted intercept and no trend, Pesaran et al. (2001)

Table 4 illustrates the results of the calculated F-statistics when each variable is considered as a dependent variable (normalized) in the ARDL-OLS regressions. The calculated F-statistics, F car (Car|Ind, FDI, POP) = 4.640954 is higher than the upper bound critical value of 4.01 at the 5% level. Moreover, none of the estimated coefficients of LnCar, LnInd, LnFdi and LnPop as represented by λ_1 , λ_2, λ_3 and λ_4 respectively is equal to 0. This is an affirmation of the presence of a long-run equilibrium relationship among the variables. Thus, the null hypothesis of no co-integration is rejected, implying a long-run co-integrating relationship among the variables when regressions are normalized on the CO_2 variable.

On the evidence of a co-integrating relationship, equation (2) was estimated using the following ARDL (2, 2, 1, 1) specification to unveil the long-run relationship. The results obtained by normalizing on per capita CO_2 emission in the long run are reported in Table 5.

Table 5: ARDL Long-run Estimation of LnCAR (2,2,1,1)

Variables	Coefficient	Std. Error	t-Statistic	Prob.
C	–14.62797	0.949170	–15.41133	0.0000
lnIND	0.235969	0.093491	2.523979	0.0166
lnFDI	–8.79E-05	5.41E-05	–1.623435	0.1140
lnPOPU	1.572144	0.256271	6.134686	0.0000

The estimated coefficients show that, both industrial production as well as population, have statistically significant positive impacts on CO_2 emissions in Bangladesh. Growing industrialization implicates a serious threat to the environment. Toxic waste from industries and factories, mostly established on the banks of the rivers, contaminates the water of the rivers as waste is not being treated by Affluent Treatment Plants (ATP), although it is mandatory for factories that dispose of toxic waste. Population growth contributes to the degradation of the environment through contaminating drinkable water and clogging the sanitation pipes. Also, numerous vehicles and traffic congestions in the capital city, increasing uses of refrigerators and air coolers are prone to CO_2 emissions. Furthermore, lnFDI has negative effects on CO_2 emissions, although it is statistically insignificant. It means inflow of FDI in Bangladesh contributes marginally in reducing CO_2 emissions. This is a result of foreign-owned enterprises' compliances with the environmental standards set by the Department of Environment (DoE).

The estimates of VECM are specified in equation (4), and are reported in Table 6.

Table 6: ARDL (2,2,1,1) vector error-correction model of LnCAR

Variables	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.036778	0.043873	0.838287	0.4105
ECM_{t-1}	−0.750210	0.238452	−3.146169	0.0045
Δ (LnCAR (-1))	0.212594	0.206878	1.027629	0.3148
Δ (LnCAR(-2))	0.025375	0.192480	0.131834	0.8963
Δ (LnIND)	0.265894	0.286973	0.926548	0.3638
Δ (LnIND(-1))	−0.043218	0.146802	−0.294395	0.7711
Δ (LnIND(-2))	0.102055	0.108315	0.942202	0.3559
Δ (FDI)	1.84E-06	6.19E-05	0.029674	0.9766
Δ (FDI(-1))	8.59E-05	7.66E-05	1.120598	0.2740
Δ (LNPOP)	1.098021	0.875253	1.254519	0.2223
Δ (LNPOP(-1))	−2.270883	0.752532	−3.017656	0.0061
R-squared	0.529096	Mean dependent var.		0.045752
Adjusted R-squared	0.324356	S.D. dependent var.		0.053969
S.E. of regression	0.044361	Akaike info criterion		−3.136711
Sum squared resid.	0.045262	Schwarz criterion		−2.642888
Log likelihood	64.32408	Hannan–Quinn criter.		−2.968303
F-statistic	2.584227	Durbin–Watson stat		2.089146
Prob. (F-statistic)	0.028935			

The estimated coefficient λ of the error-correction term (ECM $_{t-1}$) at –0.750210 is highly significant in terms of the associated t-value with the expected negative sign and its numerical magnitude indicates significant speed of adjustment towards long-run convergence. In the short–term, interactive feedback effects are positive, but statistically insignificant in terms of the insignificant associated individual t-value. The DW-value at 2.089146 indicates near absence of autocorrelation. The numerical value of shows that only 32% of the change of CO_2 emissions in Bangladesh is explained by the changes in industrial production, foreign direct investment and population. The F-statistic at 2.584227 suggests moderate interactive feedback effects within the system.

Furthermore, Figures 1 and 2 show that both the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) plots from a recursive statement of the model lie within the 5% critical bound. Thus, parameters of the VECM do not suffer from any structural instability, i.e. there is strong evidence in favor of stable parameters.

Figure 1: CUSUM of Recursive Residuals

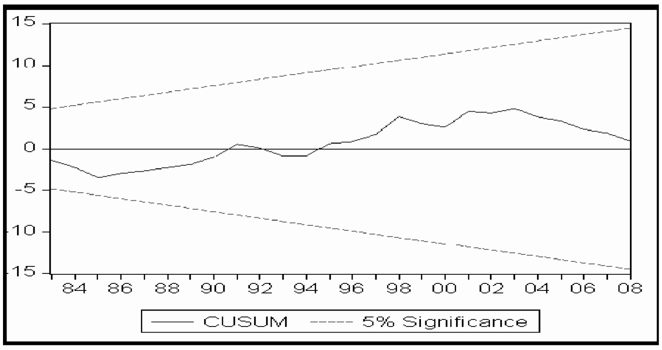
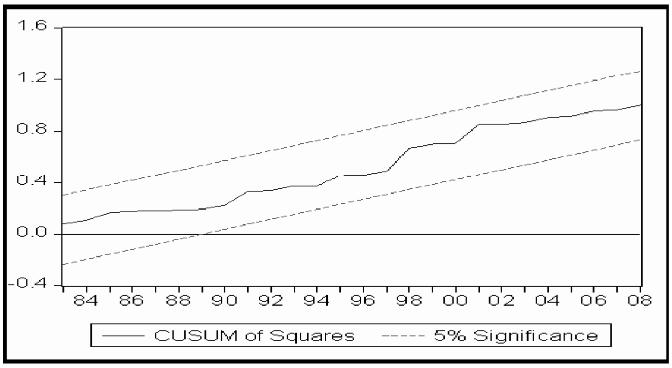


Figure 2: CUSUMSQ of Recursive Residuals



5. Conclusions and Remarks

All the variables examined in the study are non-stationary in log-levels with different orders of integration. The estimates of the ARDL model lend support to the existence of a co-integrating relationship among the variables. The estimates of the VECM depict a strongly positive long-run causal flow from industrialization and population growth to CO_2 emissions in Bangladesh while that from growth in FDI is negative and relatively subdued. There are evidences of short-run net positive interactive feedback effects among the variables.

For policy implications, Bangladesh should be poised for larger emissions of CO_2 in an early phase of industrial expansion and in the face of rapid population growth in large cities. FDI inflow should be encouraged to mitigate the problem. Once achieving a certain prescribed threshold level of per capita real GDP, the country should devote attention to improve environmental quality. At the same time, population growth should further be monitored in large cities by a wider geographic distribution of industries throughout the country. Bangladesh can draw lessons from China in these respects.

In conclusion, environmental awareness in Bangladesh is surging slowly. Although CO_2 emissions have drawn worldwide attention, other common pollutants such as sulphur dioxide (SO_2), carbon monoxide (CO), nitrogen oxide (NO_x), ground-level ozone (O_3), hydrogen sulphide (H_2S), etc., should also be mitigated in order to improve the overall environmental quality in Bangladesh.

References

1. Akaike, H. (1969) 'Fitting Auto Regression for Prediction', *Annals of the Institute of Mathematical Statistics*, Vol. 21, pp.243–247.
2. Arrow, K., Bolin, B., Costanza, R., Dasgupta, P., Folke, C., Holling, C.S., Jansson, B-O., Levin, S., Mäler, K-G., Perrings, C. and Pimentel, D. (1995) 'Economic Growth, Carrying Capacity, and the Environment', *Ecological Economics*, Vol. 15, No. 2, pp.91–95.
3. Cole, M.A. (2003) 'Development, Trade, and the Environment: How Robust is the Environmental Kuznets Curve?' *Environment and Development Economics*, Vol. 8, pp.557–580.
4. De Brueyn, S.M. (2000) '*Economic Growth and the Environment'*, Kluwer Academic Publishers, The Netherlands.
5. Dickey, D.A. and Fuller, W.A. (1981) 'Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root', *Econometrica*, Vol. 49, pp.1057–1072.

6. Dijkgraaf, E. and Vollegergn, H.R.J. (1998) 'Environmental Kuznets Revisited: Time Series versus Panel Estimation: the CO2 Case', Erasmus University Rotterdam, *OC/EB, and Research Memorandum 9806*.

7. Dinda, S. (2004) 'Environmental Kuznets Curve Hypothesis: A Survey', *Ecological Economics*, Vol., 49, No. 4, pp. 431–455.

8. Engle, R. and Granger, C.W.J. (1987) "Co-integration and Error-correction: Representation, Estimation, and Testing", *Econometrica,* Vol. 35, pp.315–329.

9. Fuller, W.A. (1996) *Introduction to Statistical Time Series*, John Wiley and Sons, New York.

10. Goldemberg, J. (1998) 'Leapfrog Energy Technologies', *Energy Policy,* Vol. 26, No. 10, pp.729–741.

11. Grossman, G.M. and Krueger, A.B. (1991) Environmental Impacts of a North American Free Trade Agreement, *NBER Working Paper* No. 3914.

12. Grossman, G.M. and Krueger, A.B. (1995) 'Economic Growth and The Environment', *Quarterly Journal of Economics,* Vol. 110, No. 2, pp.353–377.

13. Hakkio, C.S. and Rush, M. (1991) 'Cointegration: How Short is The Long Run?' *Journal of International Money and Finance,* Vol. 10, pp.571–581.

14. Johansen, S. (1988) 'Statistical Analysis of Cointegration Vectors', *Journal of Economic Dynamics and Contro*l, Vol. 12, pp.231–254.

15. Johansen, S. and Juselius, K. (1992) 'Testing Structural Hypothesis in Multivariate Cointegration Analysis of the PPP and VIP for UK', *Journal of Econometrics,* Vol. 53, Nos. 1–3, pp.211–244.

16. Johansen, S. and Juselius, K. (1999) "Maximum Likelihood Estimation and Inference on Cointegration with Applications to the Demand for Money", *Oxford Bulletin of Statistics*, Vol. 52, No. 2, pp.169–210.

17. Kwiatkowski, D., Phillips, P.C.B., Schmidt, P. and Shin, Y. (1992) 'Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root', *Journal of Econometrics*, Vol. 54, pp.159–178.

18. Lekakis, J.N. (2000) 'Environment and Development in a Southern European Country: Which Environmental Kuznets Curves?' *Journal of Environmental Planning and Management*, Vol. 43, No. 1, pp.139–153.

19. Mackinnon, J.G. (1996) 'Numerical Distribution Functions for Unit Root and Cointegration Tests', *Journal of Applied Econometrics,* Vol. 11, pp.601–618.

20. Panayotou, T. (1993) Empirical Tests and Policy Analysis of Development, ILO

Technology and Employment Programme, *Working Paper,* WP238.

21. Pesaran, M.H. (1997) 'The Role of Economic Theory in Modeling The Long-Run', *Economic Journal*, Vol. 107, pp.178–191.

22. Pesaran, M.H. and Shin, Y. (1999) 'An Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis', In Sorm, S. (Ed.): Econometrics and Economic Theory in the 20th Century: *The Ragnar Frisch Centennial Symposium*, Cambridge University Press, Cambridge.

23. Pesaran, M.H., Shin, Y. and Smith R.J. (2001) 'Bound Testing Approaches to the Analysis of Level Relationship', *Journal of Applied Econometrics,* Vol. 16, pp.289–326.

24. Stern, D.I. and Common, M.S. (2001) 'Is There an Environmental Kuznuts Curve and for Sulphur?' *Journal of Environmental Economics and Management*, Vol. 41, No. 2, pp.162–178.

25. Stern, D.I., Common, M.S. and Barbier, E.B. (1996) 'Economic Growth and Environmental Degradation: The Environmental Kuznets Curve and Sustainable Development', *World Development*, Vol. 24, No. 7, pp.1151–1160.

26. Suri, V. and Chapman, D. (1998) 'Economic Growth, Trade and the Energy: Implications for the Environmental Kuznets Curve', *Ecological Economics*, Vol. 25, No. 2, pp.195–208.

27. Unruh, G.C. and Moomaw, W.R. (1998) 'An Alternative Analysis of Apparent EKC-Type Transitions', *Ecological Economics,* Vol. 25, No. 2, pp.221–229.

28. Zhou, S. (2001) 'The Power of Cointegration Tests versus Data Frequency and Time Spans', *Southern Economic Journal*, Vol. 67, pp.906–921.