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Agriculture, trade openness and emissions: an empirical analysis and policy options*

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This article investigates the impact of sectoral production allocation, energy usage patterns and trade openness on pollutant emissions in a panel consisting of high-, medium- and low-income countries. Extended STIRPAT (Stochastic Impact by Regression on Population, Affluence and Technology) and EKC (Environmental Kuznets Curve) models are conducted to systematically identify these factors driving CO₂ emissions in these countries during the period 1980–2010. To this end, the study employs three different heterogeneous, dynamic mean group-type linear panel models and one nonlinear panel data estimation procedure that allows for cross-sectional dependence. While affluence, nonrenewable energy consumption and energy intensity variables are found to drive pollutant emissions in linear models, population is also found to be a significant driver in the nonlinear model. Both service sector and agricultural value-added levels play a significant role in reducing pollution levels, whereas industrialisation increases pollution levels. Although the linear model fails to track any significant impact of trade openness, the nonlinear model finds trade liberalisation to significantly affect emission reduction levels. All of these results suggest that economic development, and especially industrialisation strategies and environmental policies, need to be coordinated to play a greater role in emission reduction due to trade liberalisation.

Key words: agricultural value added, carbon dioxide emissions, dynamic heterogeneous panels, nonlinear panel estimation under cross-sectional dependence, trade openness.

1. Introduction

Over the past century, global average temperatures have increased by 0.8°C and are projected to rise by another 1.2–6.4°C over the next hundred years (USEPA, 2014). There is a consensus that human activities are largely responsible for these climate changes and natural calamities. Although the majority of greenhouse gases arise from burning of fossil fuels to produce energy, deforestation and industrial processes, some agricultural practices also emit gases into the atmosphere. Hence, identifying the determinants of emissions remains as a very important area of research in the energy economics literature. Two recent studies that have sought to identify the

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determinants of emissions include Sadorsky (2014) and Shahiduzzaman and Alam (2014). Both of these papers employ contemporary dynamic heterogeneous panel data modelling approaches based on a STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) analytical framework. In addition to population and affluence variables, Sadorsky (2014) considers urbanisation and energy intensity variables as proxies of technology, while Shahiduzzaman and Alam (2014) use urbanisation, energy intensity, renewable and nonrenewable energy levels as proxies of technology.

Agricultural activities are also one of the greatest contributors to global warming. Such activities are responsible for nearly one-third of global anthropogenic greenhouse gas emissions, including nitrous oxide emitted through increased fertiliser use, methane emitted via rice and livestock production, carbon dioxide emitted through the clearing of forests to create agricultural land and indirect emissions generated from the manufacture of fossil fuel-based agricultural inputs and from the processing, packaging and transporting of food (FAO, 2003). Another major factor associated with pollution is trade openness. Industrial countries have recently expressed concerns over whether 'dirty industries' migrate. In particular, such concerns have focused on a perceived loss of comparative advantage in these industries due to the application of more stringent domestic environmental regulations relative to those of developing countries. By contrast, emerging economies are highly concerned that trade liberalisation would promote specialisation in 'dirty industries', aggravating environmental damage (Dean 1992a,b). Therefore, in addition to population, affluence, service, industrialisation and disaggregated energy consumption scenarios, this article considers agricultural production and international trade within the theoretical contexts of STIRPAT and the Environmental Kuznets Curve (EKC), thus employing both linear and nonlinear methodological approaches.

This article is novel for three reasons. First, to the best of the authors' knowledge, this is one of the first articles in the literature on empirical energy economics that analyses the effect of agriculture and trade openness on CO₂ emissions. Second, this study employs both linear and nonlinear panel data procedures in identifying the determinants of CO₂ emissions. While Apergis and Payne (2014) employed threshold type nonlinear models, this study adopts the new second-generation nonlinear panel model of Kapetanios *et al.* (2014), which allows for cross-sectional dependence within a heterogeneous panel setting. Third, this article compares the importance of factors that result in pollutant emissions across low/middle-income countries (LMCs hereafter) and high-income countries (HICs hereafter).¹ The remainder of this article is organised as follows. Section 2 offers a critical review of the

¹ The clustering of the fifty-five studied countries was done according to the World Bank's raking based on 'Country and Lending Groups' that can be found from <http://data.world-bank.org/about/country-classifications/country-and-lending-groups>. While LMC countries have a per capita income of 12,615 and below, HIC countries have a per capita income of 12,616 and above.

literature related to carbon dioxide emissions, and Section 3 presents the analytical framework, data sources and empirical estimation. Section 4 presents the analysis of results, and Section 5 concludes the article with policy implications.

2. A critical review of the related literature

While there is a broad body of literature on the impacts of economic growth and/or activities on energy use, the number of studies that identify factors that affect pollutant emissions *per se* is rather small. Studies by Cole and Neumayer (2004), Hossain (2011), Liddle and Lung (2010), Martinez-Zarzoso and Maruotti (2011), Parikh and Shukla (1995), Poumanyvong and Kaneko (2010) and Sharma (2011) employ static panel data models to identify the impact of urbanisation on carbon emissions. These static panel models, however, fail to capture dynamic short- and long-term relations between the variables. Furthermore, these studies assume homogenous relationships between variables across cross sections. This assumption appears to be too stringent, especially when examining a large number of countries. Two recent studies (Sadorsky 2014; Shahiduzzaman and Alam 2014) address both of these issues through empirical estimations. However, they did not consider the possibility of nonlinear relationships that may exist among the variables. Moreover, these studies do not consider two major drivers of pollution: the role of the agricultural sector and that of international trade.

Agricultural activities release significant amounts of CO₂, CH₄ and N₂O into the atmosphere (Paustian *et al.* 2004; Cole *et al.*, 1997 and Thamo *et al.* 2013). Smith (2004) and Janzen (2004) argue that CO₂ is released largely through microbial decay or through the burning of plant litter and soil organic matter. In documenting Indonesia's deforestation-based greenhouse gas emissions, Warr and Yusuf (2011) investigate the effectiveness of a subsidy as a means of achieving greater environmental sustainability. Although numerous project reports and studies have been published in areas such as ecology, agriculture and environmental sustainability regarding the impact of agricultural activities on the environment, there is paucity of similar studies available in the resources economics literature.

Theoretically speaking, the impact of trade liberalisation on pollution levels is not clear. Two avenues of study exist. The first argues that relatively indulgent environmental regulations would denote that firms consider uses of the environment as involving a relatively cheap process. Indeed, using country-level data, Antweiler *et al.* (2001) and Copeland and Taylor (2003) document that increases in the volume of trade can result in increased pollution emissions in the United States, indicating that trade liberalisation processes may actually shift the composition of US manufacturing toward more heavily polluting industries. This positive relation between trade liberalisation and greenhouse gas emissions is also documented in Saunders

et al. (2006). The second strand of research argues that if the inverted-U hypothesis is correct (Grossman and Krueger 1993; & Selden and Song 1994), the amount of environmental damage in a country at any point in time is endogenous and depends upon the income level of the country. According to this literature, after a particular degree of income increase occurs due to factors such as free trade, higher incomes lead to a net reduction in environmental damage. However, in examining annual industry-level data for 1972 to 1994 on imports in the United States, Josh *et al.* (2004) find no evidence of any direct relation between trade liberalisation and the composition of pollution intensive industries. To our knowledge, however, no empirical study has been conducted on the impact of trade openness on pollution.

3. Analytical framework and empirical estimation

Our theoretical settings stem from two highly popular conceptual frameworks, namely the STIRPAT and EKC models. Following Dietz and Rosa (1994) and Dietz and Rosa (1997) and York *et al.* (2003), the first model (STIRPAT type) addresses sectors of domestic production (Model I) as:

$$\ln(CO_{2it}) = \ln\alpha_0 + \alpha_1\ln(POP_{it}) + \alpha_2\ln(AFL_{it}) + \alpha_3\ln(IND_{it}) + \alpha_4\ln(SER_{it}) + \alpha_5\ln(AGRI_{it}) + \ln e_{it} \quad (1)$$

where CO_2 , POP , AFL , IND , SER and $AGRI$ denote emissions, total population, GDP per capita, industrialisation, service sector contributions to GDP and agricultural sector contribution to GDP, respectively. e is the error term. The subscript i refers to countries, and t denotes time.

The second model (Model II) is related to the energy sector composition.

$$\ln(CO_{2it}) = \ln\beta_0 + \beta_1\ln(POP_{it}) + \beta_2\ln(AFL_{it}) + \beta_3\ln(REN_{it}) + \beta_4\ln(NRN_{it}) + \ln e_{it} \quad (2)$$

where REN and NRN represent renewable and nonrenewable energy consumption, respectively.

Following Martinez-Zarzoso and Maruotti (2011), the objective of the third model (Model III) is to analyse the interaction between CO_2 emissions, trade openness and income using the EKC principal.

$$\ln(CO_{2it}) = \ln\delta_0 + \delta_1\ln(POP_{it}) + \delta_2\ln(AFL_{it}) + \delta_3\ln(AFL_{it})^2 + \alpha_4\ln(OPN_{it}) + \alpha_5\ln(OPN_{it})^2 + \delta_6\ln(ENI_{it}) + \ln e_{it} \quad (3)$$

where OPN and ENI indicate trade openness and energy intensity, respectively.

Annual data for 1980 to 2010 for a set of 53 countries consisting of 30 low-medium-income (LMC) and 23 high-income (HIC), countries were used (Appendix Table S1). These periods were selected due to data availability. Variables used in this study are carbon dioxide emissions in kilo tons; population in numbers; affluence in constant 2005 US\$ per capita GDP; industrialisation, service and agriculture contributions to GDP; renewable and nonrenewable energy consumption in quadrillion BTU (QBTU); trade openness as (export+import)/GDP (following Squalli and Wilson 2011); and energy intensity as energy use (kg of oil equivalent) per \$1 million constant GDP (following Jones 1991 & Sadorsky 2013). All data, except those for renewable and nonrenewable energy, were obtained from the World Development Indicators online database produced by the World Bank. Renewable and nonrenewable energy data were obtained from the Energy Information Administration (EIA) online database. Prior to the estimation, all data were transformed into their logarithmic form.

Based on the above-specified relationships between variables, this analysis employs both linear and nonlinear panel data estimation procedures to identify the determinants of pollutant emissions. As assuming that all factors affecting emissions across all 53 countries are homogenous is quite unrealistic, the above models Equations (1–3), are estimated using the following contemporary techniques with heterogeneous slope coefficients: mean group (MG) estimators (Pesaran and Smith 1995; Pesaran 1997) and variants of MG estimators such as Pesaran's (2006) Common Correlated Effects Mean Group (CCEMG) estimator and the Augmented Mean Group (AMG) approach of Eberhardt and Teal (2010) and Bond and Eberhardt (2009). In addition to allowing for heterogeneous slope coefficients across group members, these estimators also account for correlations across panel members (*i.e.*, cross-sectional dependence). These models are designed for 'moderate-T, moderate-N' macro panels, wherein the term 'moderate' pertains to approximately 15 time-series/cross-sectional observations (Eberhardt and Teal 2010). However, here, we employ three panels with $N = 53$, 30 23 and $T = 30$. Equations (1), (2) and (3) can be specified as dynamic panel models of the following forms:

$$CO_{2it} = \alpha_i CO_{2it-1} + \beta_{1i} POP_{it} + \beta_{2i} POP_{it-1} + \beta_{3i} AFL_{it} + \beta_{4i} AFL_{it-1} + \beta_{5i} IND_{it} + \beta_{6i} IND_{it-1} + \beta_{7i} SER_{it} + \beta_{8i} SER_{it-1} + \beta_{9i} AGRI_{it} + \beta_{10i} AGRI_{it-1} + \rho_{1i} + \epsilon_{1it} \quad (4)$$

$$CO_{2it} = \lambda_i CO_{2it-1} + \sigma_{1i} POP_{it} + \sigma_{2i} POP_{it-1} + \sigma_{3i} AFL_{it} + \sigma_{4i} AFL_{it-1} + \sigma_{5i} REN_{it} + \sigma_{6i} REN_{it-1} + \sigma_{7i} NRN_{it} + \sigma_{8i} NRN_{it-1} + \rho_{2i} + \epsilon_{2it} \quad (5)$$

$$CO_{2it} = \chi_i CO_{2it-1} + \delta_{1i} POP_{it} + \delta_{2i} POP_{it-1} + \delta_{3i} AFL_{it} + \delta_{4i} AFL_{it-1} + \delta_{5i} AFL_{it}^2 + \delta_{6i} AFL_{it-1}^2 + \delta_{7i} OPN_{it} + \delta_{8i} OPN_{it-1} + \delta_{9i} OPN_{it}^2 + \delta_{10i} OPN_{it-1}^2 + \delta_{11i} ENI_{it} + \delta_{12i} ENI_{it-1} + \rho_{3i} + \epsilon_{3it} \quad (6)$$

Equations (4), (5) and (6) are examples of autoregressive distributed lag (ARDL) models of order one. We can, nonetheless, increase the lag on variables on the right hand side. We also apply pooled mean group methodological approaches to explore long- and short-run Granger causalities across the variables. The residuals, obtained from the long-run estimates, are used as dynamic error correction terms.

The assumption of linearity, however, may not always hold. Hence, we also employ a nonlinear panel data estimation model recently developed by Kapetanios *et al.* (2014) [KMS (2014), hereafter]. This model is superior in that it can endogenously generate both ‘weak’ and ‘strong’ cross-sectional dependence. KMS (2014) proposed a threshold dynamic model for a multitude of agents (*i.e.*, countries).

Following KMS (2014), we estimated the full multivariate nonlinear panel model under cross-sectional dependence as follows:

$$y_{it} = \beta' x_{it} + \varepsilon_{it}, i = 1, \dots, N, t = 1, \dots, T, \quad (7)$$

$$\varepsilon_{it} = v_{it} - u_{it}, \quad (8)$$

$$u_{it} = \alpha_i + \rho \tilde{u}_{it}(r) + \lambda_i' f_t, \quad (9)$$

$$\tilde{u}_{it} = \frac{1}{m_{it}} \sum_{j=1}^N \ell(|u_{t-1}^* - u_{jt-1}| \leq r) u_{jt-1}, \quad (10)$$

where $m_{it} = \sum_{j=1}^N \ell(|u_{i,t-1} - u_{j,t-1}| \leq r)$,

where y_{it} denotes emissions; x_{it} is a vector of independent variables; α_i is an (unobserved) individual-specific effect; f_t is a vector of heterogeneous loading; and $\tilde{u}_{it}(r)$ represents a cluster effect that is equal to the average labour market efficiency level of the countries, which is close to the frontier where $u_{it}^* = \min_j (u_{jt} - 1)$ and where v_{it} is an idiosyncratic disturbance. $\{i, t\}_{t=1}^T$ is an error process, $\ell(\cdot)$ is the indicator function and $-1 < \rho < 1$. Model (10) is evidently quite similar to threshold autoregressive (TAR) models. Unlike a straightforward extension to a panel data setting whereby individual countries would not have (any) interactions, the nonlinearity in Equation (10) is inherently cross-sectional. We further estimate \hat{r} and $\hat{\rho}$ together by minimizing,

$$V(r, \rho) = \min_{r, \rho} \sum_{t=1}^N \sum_{t=1}^T (\hat{e}_{it} - \rho \frac{1}{m_{it}} \sum_{j=1}^N \ell(|\hat{e}_{t-1}^* - \hat{e}_{jt-1}| \leq r) \hat{e}_{jt-1}) \quad (11)$$

$$\hat{e}_{it} = \max_i(\hat{u}_{it}) - (\hat{u}_{it}) = \max_i(\hat{\alpha}_i + \hat{\rho}u_{it}(\hat{r}) + \hat{\lambda}_i'f_t) \quad (12)$$

4. Results and discussion

At the outset, we implement Dickey and Fuller (1979), Philips and Perron (1988), Breitung (2000), Levin *et al.* (2002) and Im *et al.* (2003) tests to investigate whether the series follows a unit root process. The results for CO_2 , POP , AFL , IND , SER , $AGRI$, REN , NRN , AFL^2 , OPN , OPN^2 and ENI are reasonably consistent, indicating that the variables contain unit roots at their levels.²

The results of such tests are not always reliable when variables contain cross-sectional dependence and/or structural breaks. The following three tests have been used to identify cross-sectional dependence in the contemporary panel data econometric literature: those by Friedman (1937), Frees (1995) and Pesaran (2004).³ The results from these tests highlight that there is sufficient evidence to reject the null hypothesis of cross-sectional independence. Hence, quite reasonably, the unit root test's allowance of cross-sectional dependence is warranted. Pesaran's (2007) CIPS ($z(t\text{-bar})$) test for the unit root is adopted for this purpose.⁴ The results of the CIPS tests with constant terms indicate that all of the variables studied contain unit roots at their levels and are stationary in their first difference.

It is not yet sufficient to conclude that all of the series follow a nonstationary process, as any of these series may have undergone structural breaks. Hence, panel unit root tests with structural breaks were employed following the methodological approach presented by Carrión-i-Silvestre *et al.* (2005). The results are presented in Table 1. The results indicate that the null hypothesis of stationarity is rejected for all of the variables and in both homogeneous and heterogeneous long-run versions of the test. Furthermore, for all of the variables in the model, the following two years appear to prominently characterise the break period: 1998 and 2009. The year 2009 marks the third year following the start of the US banking and financial crisis of 2007. The financial crisis began in the United States in 2007 and affected financial institutions in numerous OECD countries. It was only when the crisis developed into a global economic recession that developing and emerging market economies were affected, mainly through the trade channel and in some cases through falling worker remittances. The following three major global financial and economic events may have triggered the year 1998 as a starting date: (i) the Asian financial crisis, (ii) the start of the Argentinian great depression and (iii) the Russian financial crisis.

² The results of these tests are not reported due to space constraints. They can be furnished upon request.

³ Same as footnote 2.

⁴ Same as footnote 2.

Table 1 Panel unit root test with structural breaks

Variables	Carrión-i-Silvestre <i>et al.</i> [LM(λ)]		Break location (T_b)
	Test	Bootstrap critical value (5%)	
CO ₂			
Ψ_{τ}	-5.557**	-3.248	1990
Ψ'_{LM}	-5.453**	-3.248	
POP			
Ψ_{τ}	-4.554**	-3.248	2009
Ψ'_{LM}	-4.497*	-3.248	
AFL			
Ψ_{τ}	-4.752**	-3.382	2009
Ψ'_{LM}	-4.688*	-3.382	
IND			
Ψ_{τ}	-6.121**	-3.316	2009
Ψ'_{LM}	-5.985**	-3.316	
SER			
Ψ_{τ}	-13.752**	-3.400	1998
Ψ'_{LM}	-12.332**	-3.400	
AGRI			
Ψ_{τ}	-4.152**	-3.227	2009
Ψ'_{LM}	-4.109**	-3.227	
REN			
Ψ_{τ}	-5.713**	-3.374	2009
Ψ'_{LM}	-5.600**	-3.374	
NRN			
Ψ_{τ}	-5.421**	-3.370	2009
Ψ'_{LM}	-5.325**	-3.370	
OPN			
Ψ_{τ}	-6.935**	-3.401	1998
Ψ'_{LM}	-6.738**	-3.401	
AFL			
Ψ_{τ}	-4.778**	-3.364	2009
Ψ'_{LM}	-4.712**	-3.364	
OPN			
Ψ_{τ}	-6.931**	-3.401	1998
Ψ'_{LM}	-6.733**	-3.401	
ENI			
Ψ_{τ}	-5.861	-3.356	1998
Ψ'_{LM}	-5.740	-3.356	

Note: The number of unknown structural breaks is set to five. The null of the LM (λ) test implies stationarity. The Gauss procedure was conducted based on the code provided by Ng and Perron (Ng and Perron 2001). The tests were computed using the Bartlett kernel, and all of the bandwidth and lag lengths were chosen according to $4(T/100)^{2/9}$. The bootstrap critical values allow for cross-sectional dependence. Individual country break dates were also computed (available upon request).

According to the unit root tests conducted under varying specifications, there is substantial evidence that all of the variables under investigation are nonstationary at levels containing unit roots. Therefore, panel cointegration tests are employed to study the long-run equilibrium across the variables. To test for the likelihood of cointegrating relationships, we conducted three alternative cointegration tests presented by Westerlund (2007) and Bai and Perron (2003) and Johansen Fisher tests proposed by Maddala and Wu (1999).

According to the Westerlund (2007) test results, both the group *t*- and panel *t*-tests reject the null hypothesis of non-cointegration for both models across all three different panels (Appendix Table S2). Similarly, the results of the Johansen and Fisher tests from both trace and eigenvalue tests reveal the presence of cointegration at the 1% significance level, and the Bai and Perron (2003) cointegration test results reveal the presence of cointegrating relationships around a broken intercept.⁵ Hence, estimating long-run elasticities through both linear and nonlinear models under cross-sectional dependence appears to be essential.

Based on three heterogeneous panel estimations, the long-run elasticities are reported in Table 2. The empirical estimates reveal that affluence (per capita income) elasticity with respect to emissions is positive and statistically significant, while across all models, population levels are statistically insignificant. These results contradict those of Fan *et al.* (2006), Poumanyong and Kaneko (2010), Liddle (2011) and Shahiduzzaman and Alam (2014) who claim that in the long run, populations contribute more to increased CO₂ emissions than economic growth. For the entire panel, the affluence elasticity level ranges from 0.34 to 0.84, for high-income countries, this range varies from 0.21 to 0.61, and for the low/medium-income countries, the range is slightly higher at 0.53 to 0.82.

In Model I (sectoral STIRPAT), the service sector plays a major role in reducing emissions in HIC countries, as elasticity levels range from -0.78 to -1.38 . In the case of Model II and in terms of energy composition levels, nonrenewable energy induces emissions across all three panels, with elasticity levels at approximately 0.58 for the full panel, at 0.70 to 0.74 for the HIC countries, and slightly lower at 0.42 to 0.45 for the LMC countries. Shahiduzzaman and Alam (2014) also find a positive and statistically significant effect of nonrenewable energy on emissions. However, their elasticity estimate was much higher (1.038).

Renewable energy, nonetheless, plays a negative and statistically significant role only in the case of the HIC countries with elasticities of roughly -0.07 . While this finding is consistent with Shahiduzzaman and Alam (2014), it opposes what was found in Apergis and Payne (2010) and Memedovic and Iapadre (2010). Interfuel substitution towards a cleaner mix of fuels and technologies is also documented in Shahiduzzaman and Alam (2014) and Bloch *et al.* (2015) in contexts of Australia and China, respectively. This result, nevertheless, substantiates the argument that an increased usage of renewable energy reduces pollutant emissions in the case of the developed countries in the long-term. With respect to EKC and in terms of model III, the signs of the estimated coefficients conform to those of the Kuznets Curve model, though none of the elasticities for affluence and openness are statistically significant for either the full or LMC panel. For the HIC countries and under the two estimation procedures, the EKC hypothesis

⁵ Same as footnote 2.

Table 2 Pollutant emission elasticities

Elasticity	Model I			Model II			Model III		
	MG	CCEMG	AMG	MG	CCEMG	AMG	MG	CCEMG	AMG
Full Pnl.									
POP	-1.27 (0.45)	-12.55 (0.26)	-0.73 (0.68)	-0.85 (0.57)	-5.16 (0.17)	-0.25 (0.87)	-1.04 (0.58)	-3.11 (0.29)	0.14 (0.94)
AFL	0.69*** (0.00)	0.84*** (0.00)	0.77*** (0.00)	0.34*** (0.00)	0.61*** (0.00)	0.42*** (0.00)	2.67 (0.78)	4.87 (0.33)	-0.25 (0.97)
IND	-0.08 (0.54)	-0.02 (0.80)	-0.02 (0.82)						
SER	-0.54 (0.11)	-0.24 (0.45)	-0.41 (0.19)						
AGRI	0.08 (0.33)	0.05 (0.39)	0.10 (0.19)						
REN				-0.04 (0.27)	-0.05 (0.13)	-0.05* (0.09)			
NRN				0.58*** (0.00)	0.59*** (0.00)	0.58*** (0.00)			
OPN							41.73 (0.32)	-9.53 (0.22)	41.71 (0.32)
ENI							1.1*** (0.00)	1.0*** (0.00)	1.1*** (0.00)
AFL ²							-0.32 (0.61)	-0.22 (0.43)	-0.09 (0.84)
OPN ²							-1.48 (0.32)	0.35 (0.21)	-1.49 (0.32)
HIC Pnl.									
POP	0.15 (0.86)	-0.54 (0.60)	-0.03 (0.97)	0.72 (0.35)	0.10 (0.93)	0.79 (0.32)	1.06 (0.12)	2.12** (0.02)	0.86 (0.23)
AFL	0.58*** (0.00)	0.61** (0.03)	0.45*** (0.00)	0.21** (0.02)	0.35*** (0.01)	0.27*** (0.00)	-17.7** (0.06)	-6.47 (0.17)	-6.96 (0.22)
IND	-0.33*** (0.03)	-0.07 (0.59)	-0.18 (0.13)						
SER	-1.38*** (0.02)	-0.78* (0.08)	-1.09** (0.03)						
AGRI	-0.09 (0.16)	-0.071* (0.09)	-0.07 (0.26)						
REN				-0.07*** (0.00)	-0.07*** (0.00)	-0.07*** (0.00)			
NRN				0.75*** (0.00)	0.74*** (0.00)	0.70*** (0.00)			
OPN							-1.11 (0.84)	-6.06 (0.16)	-4.76 (0.26)
ENI							1.0*** (0.00)	1.1*** (0.00)	1.0*** (0.00)
AFL ²							0.90** (0.05)	0.38* (0.09)	0.387 (0.16)
OPN ²							0.03 (0.852)	0.22 (0.156)	0.18 (0.246)
LMC Pnl.									
POP	-2.38 (0.41)	-8.21 (0.24)	-1.98 (0.49)	-2.06 (0.43)	-7.63* (0.05)	-1.55 (0.55)	-2.66 (0.42)	-5.74 (0.32)	-1.96 (0.54)
AFL	0.78*** (0.00)	0.76*** (0.00)	0.82*** (0.00)	0.46*** (0.00)	0.68*** (0.00)	0.53*** (0.00)	18.14 (0.19)	-11.29 (0.46)	20.53* (0.09)
IND	0.12 (0.52)	0.05 (0.67)	0.05 (0.77)						

Table 2 (Continued)

Elasticity	Model I		Model II		Model III	
	MG	CCEMG	AMG	MG	CCEMG	AMG
SER	0.11 (0.75)	0.38 (0.19)	0.09 (0.76)			
AGRI	0.21 (0.11)	0.09 (0.19)	0.21* (0.08)			
REN				-0.02 (0.77)		
NRN				0.45*** (0.00)		
OPN					-0.02 (0.79)	
ENI					0.42*** (0.00)	
AFL ²						-0.06 (0.23)
OPN ²						0.45*** (0.00)
				74.57 (0.31)	-123.18 (0.29)	103.48 (0.31)
				1.2*** (0.00)	0.74** (0.02)	1.1*** (0.00)
				-1.26 (0.22)	0.95 (0.42)	-1.43 (0.12)
				-2.65 (0.31)	4.41 (0.29)	-3.69 (0.31)

Note: ***, ** and * indicate that the test statistic is significant at the 1%, 5% and 10% levels, respectively. Elasticities are based on the Pesaran and Smith (1995) Mean Group estimator (MG), the Pesaran (2006) Common Correlated Effects Mean Group estimator (CCEMG) and on the Augmented Mean Group estimator (AMG) presented in Eberhardt and Teal (2010). Figures in parentheses denote p-values.

appears to hold. Energy intensity levels, nonetheless, have a significantly positive effect on pollutant emissions across all three panels.

Next, we perform Granger causality tests using the pooled mean group approach. The results, presented in Table 3, show that the negative signs across all error correction terms confirm the cointegration findings of the active role of the short-term adjustment mechanism towards the long-run equilibrium. With respect to full panel affluence, renewable, nonrenewable energy and energy intensity Granger levels cause pollutant emissions. Affluence, service sector, renewable energy, nonrenewable energy and energy intensity Granger levels cause emissions in high-income countries as well, while in the case of LMCs, affluence, service value added, agriculture value added, renewable energy, nonrenewable energy and energy intensity Granger values cause pollutant emissions.

As the model specifications do not always follow a linear process, we also perform a nonlinear panel data estimation procedure to ensure the robustness of the previous findings. There are other models of nonlinear panel data estimation, such as that of Gonzalez *et al.* (2005) as implemented in Apergis and Salim (2015). However, the KMS (2014) model allows for cross-sectional dependence, which has been tested positively with regards to panel datasets. The results of these nonlinear estimations are reported in Appendix Table S3.

All spatial parameters of the KMS (2014) estimations are significant and less than one, indicating that the least squares estimators are consistent [theorem 1 in KMS, 2014]. According to these results, both population and affluence levels have significant positive effects on emissions. Although each model provides different magnitudes of elasticities for both population and GDP per capita, the coefficient for total population is greater than that for affluence across all three models. Unlike the linear panel model results, the nonlinear results are in line with those provided by Fan *et al.* (2006), Poumanyong and Kaneko (2010), Liddle (2011) and Shahiduzzaman and Alam (2014). More specifically, for the sectoral STIRPAT Model I, while industrialisation signals positive statistically significant elasticity, both service and agricultural value added signal negative and statistically significant elasticity across all three panels, indicating that industrialisation induces pollutant emissions across all countries, while both service sector and agricultural activities help reduce emissions.

As expected, renewable energy has a statistically significant and negative elasticity effect, while nonrenewable energy elasticity is positive. Hence, across all panels, renewable energy consumption reduces pollution levels, while nonrenewable energy helps increase pollution levels. The Model III results show that EKC phenomena exist across all three panels as far as the relationship between affluence and pollution is concerned. While energy intensity positively affects emissions, higher trade openness also helps reduce emissions significantly. Thus, it could be argued that the nonlinear model performs better in the light of the existing literature and current effectiveness

Table 3 Panel causality test based on pooled mean group analyses (PMG)

Depnt. variable	Sources of causation [short run (χ^2)]										Long run	
	Δ POP	Δ AFL	Δ IND	Δ SER	Δ AGRI	Δ REN	Δ NRN	Δ OPN	Δ AFL ²	Δ OPN ²	Δ ENI	ECT
Full Pnl.												
Mdl. I	0.48 (0.49)	21.7 (0.00)	0.14 (0.71)	0.59 (0.44)	0.82 (0.36)							-1.22 (0.00)
Mdl. II	1.19 (0.27)	5.74 (0.02)				8.02 (0.01)	134.85 (0.00)	2.50 (0.11)	1.96 (0.16)	2.71 (0.09)	36.89 (0.00)	-0.04 (0.00)
Mdl. III	0.45 (0.50)	2.41 (0.12)										-0.14 (0.00)
HIC Pnl.												
Mdl. I	3.17 (0.07)	6.11 (0.01)	0.23 (0.63)	2.99 (0.08)	0.33 (0.56)							-0.15 (0.03)
Mdl. II	0.14 (0.70)	7.30 (0.00)				18.62 (0.00)	177.97 (0.00)	0.02 (0.88)	0.36 (0.54)	0.03 (0.86)	190.8 (0.00)	-0.04 (0.00)
Mdl. III	0.42 (0.51)	0.68 (0.40)										-0.06 (0.00)
LMC Pnl.												
Mdl. I	2.90 (0.08)	10.29 (0.00)	0.74 (0.39)	2.82 (0.09)	36.17 (0.00)							-1.16 (0.00)
Mdl. II	0.14 (0.70)	7.30 (0.00)				18.62 (0.00)	177.97 (0.00)	0.94 (0.33)	0.26 (0.60)	0.92 (0.34)	11.25 (0.00)	-0.036 (-0.02)
Mdl. III	0.86 (0.35)	0.43 (0.51)										-0.14 (0.00)

Note Chi-square tests were conducted for short-run analyses. *p*-values are provided in the parentheses. ETC denotes estimated error correction terms. The Schwarz information criterion (SIC) was used to determine the optimum lag length.

of econometric tests, denoting the appropriateness of adopting nonlinear models in energy economics research.

4.1 Robustness tests: estimations across regimes

To check the robustness of our results and given our identification of break points above (Table 1), we contribute to the literature by examining how nonlinear interactions among carbon dioxide emissions and the set of independent variables change as economies move through the different regimes defined by break points. In doing so, we estimate a structural regime-threshold model. This modification is inspired by the seminal contributions of Enders and Granger (1998) and Hansen (1999), which allow regimes to be identified by one or multiple threshold variables.⁶ According to the results, the signs of all coefficients under both regimes (before and after the break dates) for all three models appear thus far to be largely consistent with what we have obtained using linear and nonlinear modes. More importantly, most of them are significant.

5. Conclusions and policy implications

This article attempts to analyse the effect of sectoral production allocation, energy usage patterns and trade openness on pollutant emissions for a panel of 53 countries consisting of high- and low/medium-income countries based on a complete system of three equations following STIRPAT and EKC hypotheses. In performing this task, we employ linear heterogeneous dynamic mean group models and nonlinear panel data models that allow for cross-sectional dependence.

According to the linear panel estimates, affluence, nonrenewable energy consumption and energy intensity are the major drivers behind pollutant emissions across all panels, and population elasticity was found to be statistically insignificant. By contrast, in nonlinear estimations, population elasticity was found to be statistically significant and greater than its affluence counterpart. These results are consistent with those of previous studies, that is Fan *et al.* (2006), Poumanyvong and Kaneko (2010), Liddle (2011) and Shahiduzzaman and Alam (2014). In both linear and nonlinear estimations, the service sector value added and renewable energy adoption play significant roles in reducing pollution in high-income countries. By contrast, the nonlinear estimations show that industrialisation increases pollution levels and that both service and agriculture value added help reduce emissions. Furthermore, across all panels, renewable energy consumption reduces pollution levels, and nonrenewable energy helps increase pollution levels. Both linear and nonlinear models suggest the presence of the EKC hypothesis, while energy intensity is a major driver of emissions across all

⁶ Same as footnote 2.

panels. While the linear models fail to show any significant effect of trade openness, the results of the nonlinear model show that trade liberalisation significantly influences emissions reduction.

Our results also have substantial policy implications in regard to pollutant emissions patterns across the world, irrespective of income levels. Reducing the consumption of nonrenewable energy, increasing the adoption of less energy intensive technologies and encouraging greater value addition from the service sector would lead to a 'greener' planet as far as emissions are concerned. The linear model further showed that renewable energy has already had a positive impact on emission reduction scenarios in developed countries. This may encourage policy news in the emerging world that proactively accelerates the adoption of cleaner technologies in daily life (Salim and Rafiq 2012). Furthermore, the significant role of service sector value added and renewable energy adoption in reducing emissions is indicative of the success of transitions in the production process that have taken place in developed countries. The environmental benefit of this shift toward a cleaner services sector from fossil fuel-dependent manufacturing is now reflected in the empirical results with respect to HIC countries. The nonlinear model, however, creates more avenues for designing policy instruments. In particular, it will allow us to adopt policies that encourage greater trade openness and renewable energy adoption to further reduce greenhouse gas emissions. The main premise of our findings is that economic development, in particular industrialisation strategies and environmental policies, must be coordinated to play a greater role in the emission reduction of trade liberalisation around the world.

References

- Antweiler, W., Copeland, B.R. and Taylor, M.S. (2001). Is free trade good for the environment?, *American Economic Review* 91, 877–908.
- Apergis, N. and Payne, J.E. (2010). Renewable energy consumption and economic growth: evidence from panel OECD countries, *Energy Policy* 38, 656–660.
- Apergis, N. and Payne, J.E. (2014). Renewable energy, output, CO₂ emissions, and fossil fuel prices in Central America: evidence from a nonlinear panel smooth transition vector error correction model, *Energy Economics* 42, 226–232.
- Apergis, N. and Salim, R. (2015). Renewable energy consumption and unemployment: evidence from a sample of 80 countries and nonlinear estimates, *Applied Economics* 47, 5614–5633.
- Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models, *Journal of Applied Econometrics* 19, 1–22.
- Bloch, H., Rafiq, S. and Salim, R.A. (2015). Economic growth with coal, oil and renewable energy consumption in China: prospects for fuel substitution, *Economic Modelling* 44, 104–115.
- Bond, S. and Eberhardt, M. (2009). Cross-section dependence in nonstationary panel models: A novel estimator, Paper presented in the Nordic Econometrics Conference in Lund, Sweden.
- Breitung, J. (2000). The local power of some unit root tests for panel data, *Advanced Econometrics* 15, 161–178.

- Carrión-i-Silvestre, J.L., Barrio, T.D. and Lopez-Bazo, E. (2005). Breaking the panels. An application to the GDP per capita, *Econometrics Journal* 8, 159–175.
- Cole, M.A. and Neumayer, E. (2004). Examining the impact of demographic factors on air pollution, *Population Development Review* 2, 5–21.
- Cole, C.V., Duxbury, J., Freney, J., Heinemeyer, O., Minami, K., Mosier, A., Paustian, K., Rosenberg, N., Sampson, N., Sauerbeck, D. and Zhao, Q. (1997). Global estimates of potential mitigation of greenhouse gas emissions by agriculture, *Nutrient Cycling in Agroecosystems* 49, 221–228.
- Copeland, B.R. and Taylor, M.S. (2003). *Trade and the Environment: Theory and Evidence*. Princeton University Press, Princeton, New Jersey 08540.
- Dean, J.M. (1992a). Trade and the environment: a survey of the literature, in Bank, T.W. (ed.), *World Development Report 1992*. World Development Report office, World Bank, Washington, pp. 13–17.
- Dean, J.M. (1992b). Trade policy and the environment: developing country concerns. OECD, The Environment Directorate.
- Dickey, D.A. and Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association* 74, 427–431.
- Dietz, T. and Rosa, E.A. (1994). Rethinking the environmental impacts of population, affluence and technology, *Human Ecology Review* 1, 277–300.
- Dietz, T. and Rosa, E.A. (1997). Effects of population and affluence on CO₂ emissions, *Proceedings of the National Academy of Sciences* 94, 175–179.
- Eberhardt, M. and Teal, F. (2010). Productivity analysis in global manufacturing production, Economics Series Working Papers. University of Oxford.
- Enders, W. and Granger, C.W.J. (1998). Unit root tests and asymmetric adjustment with an example using the term structure of interest rates, *Journal of Business and Economic Statistics* 16, 304–311.
- Fan, Y., Liu, L.-C., Wu, G. and Wei, Y.-M. (2006). Analyzing impact factors of CO₂ emissions using the STIRPAT model, *Environmental Impact Assessment Review* 26, 377–395.
- FAO (2003). *World Agriculture: Towards 2015/2030*. Food and agriculture organization of the United Nations, Rome.
- Frees, E.W. (1995). Assessing cross-sectional correlation in panel data, *Journal of Econometrics* 69, 393–414.
- Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance, *Journal of the American Statistical Association* 32, 675–701.
- Gonzalez, A., Terasvirta, T. and Dijk, D. (2005). Panel smooth transition regression models, Working Paper Series in Economics and Finance. Stockholm School of Economics, Sweden.
- Grossman, G.M. and Krueger, A.B. (1993). *Environmental Impacts of a North American Free Trade Agreement*. MIT Press, Cambridge, MA.
- Hansen, B.E. (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference, *Journal of Econometrics* 93, 345–368.
- Hossain, M. (2011). Panel estimation for CO₂ emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries, *Energy Policy* 39, 6991–6999.
- Im, K., Pesaran, M.H. and Shin, Y. (2003). Testing for unit root in heterogeneous panels, *Journal of Econometrics* 115, 53–74.
- Janzen, H.H. (2004). Carbon cycling in earth systems - a soil science perspective, *Agriculture, Ecosystems and Environment* 104, 399–417.
- Jones, D.W. (1991). How urbanization affects energy-use in developing countries, *Energy Policy* 1991, 621–630.
- Josh, E., Arik, L. and Jenny, M. (2004). Trade liberalization and pollution havens, *The BE Journal of Economic Analysis and Policy* 3, 1–24.
- Kapetanios, G., Mitchell, J. and Shin, Y. (2014). A nonlinear panel data model of cross-section dependence, *Journal of Econometrics* 179, 134–157.

- Levin, A., Lin, C.-F. and Chu, C.S.J. (2002). Unit root tests in panel data: asymptotic and finite sample properties, *Journal of Econometrics* 108, 1–24.
- Liddle, B. (2011). Consumption-driven environmental impact and age structure change in OECD countries: a cointegration-STIRPAT analysis, *Demographic Research* 24, 749–770.
- Liddle, B. and Lung, S. (2010). Age-structure, urbanization and climate change in developing countries: revisiting STIRPAT for disaggregated population and consumption related environmental impacts, *Population Environment* 31, 317–343.
- Maddala, G.S. and Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test, *Oxford Bulletin of Economics and Statistics* 61, 631–652.
- Martinez-Zarzoso, I. and Maruotti, A. (2011). The impact of urbanization on CO₂ emissions: evidence from developing countries, *Ecological Economics* 70, 1344–1353.
- Memedovic, O. and Iapadre, L. (2010). Structural change in the world economy: Main features and trends, in: Branch, R.A.S. (ed.), Working paper United Nations Industrial Development Organization, Vienna.
- Ng, S. and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power, *Econometrica* 69, 1519–1554.
- Parikh, J. and Shukla, V. (1995). Urbanization, energy use and greenhouse effects in economic development - results from a cross-sectional study of developing countries, *Global Environment Change* 5, 87–103.
- Paustian, K., Babcock, B.A., Hatfield, J., Lal, R., McCarl, B.A., McLaughlin, S., Mosier, A., Rice, C., Robertson, G.P., Rosenberg, N.J., Rosenzweig, C., Schlesinger, W.H. and Zilberman, D. (2004). Agricultural mitigation of greenhouse gases: Science and policy options, CAST (Council on Agricultural Science and Technology) Report R141 2004, ISBN 1-887383-26-3, p. 120.
- Pesaran, M.H. (1997). The role of economic theory in modelling the long run, *Economic Journal* 107, 178–191.
- Pesaran, M.H. (2004). General diagnostic tests for cross section dependence in panels, Cambridge Working Papers in Economics. University of Cambridge (June).
- Pesaran, M.H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure, *Econometrica* 74, 967–1012.
- Pesaran, M.H. (2007). A simple panel unit root test in the presence of crossection dependence, *Journal of Applied Economics* 22, 265–312.
- Pesaran, M.H. and Smith, R.P. (1995). Estimating long-run relationships from dynamic heterogeneous panels, *Journal of Economic* 68, 79–113.
- Philips, P.C.B. and Perron, P. (1988). Testing for a unit root in time series regression, *Biometrika* 75, 12.
- Poumanyong, P. and Kaneko, S. (2010). Does urbanization lead to less energy use and lower CO₂ emissions? A cross-country analysis, *Ecological Economics* 70, 434–444.
- Sadorsky, P. (2013). Do urbanization and industrialization affect energy intensity in developing countries?, *Energy Economics* 37, 52–59.
- Sadorsky, P. (2014). The effect of urbanization on CO₂ emissions in emerging economies, *Energy Economics* 41, 147–153.
- Salim, R.A. and Rafiq, S. (2012). Why do some emerging economies proactively accelerate the adoption of renewable energy?, *Energy Economics* 34, 1051–1057.
- Saunders, C., Wreford, A. and Cagatay, S. (2006). Trade liberalisation and greenhouse gas emissions: the case of dairying in the European Union and New Zealand, *Australian Journal of Agricultural and Resource Economics* 50, 538–555.
- Selden, T.M. and Song, D. (1994). Environmental quality and development: is there a Kuznets Curve for air pollution emissions?, *Journal of Environmental Economics and Management* 27, 147–162.
- Shahiduzzaman, M. and Alam, K. (2014). Interfuel substitution in Australia: a way forward to achieve environmental sustainability, *Australian Journal of Agricultural and Resource Economics* 58, 22–42.

- Sharma, S.S. (2011). Determinants of carbon dioxide emissions: empirical evidence from 69 countries, *Applied Energy* 88, 376–382.
- Smith, P. (2004). Engineered biological sinks on land, in Field, C.B. and Raupach, M.R. (eds), *The Global Carbon Cycle. Integrating Humans, Climate, and the Natural World*. SCOPE 62, Island Press, Washington D.C., pp. 479–491.
- Squalli, J. and Wilson, K. (2011). A new measure of trade openness, *The World Economy* 34, 1745–1770.
- Thamo, T., Kingwell, R.S. and Pannell, D.J. (2013). Measurement of greenhouse gas emissions from agriculture: economic implications for policy and agricultural producers, *Australian Journal of Agricultural and Resource Economics* 57, 234–252.
- USEPA. (2014). Climate Change: Basic Information, Available from URL: <http://www.epa.gov/climatechange/basics/> [accessed 24 Jun 2014].
- Warr, P. and Yusuf, A.A. (2011). Reducing Indonesia's deforestation-based greenhouse gas emissions, *Australian Journal of Agricultural and Resource Economics* 55, 297–321.
- Westerlund, J. (2007). Testing for error correction in panel data, *Oxford Bulletin of Economics and Statistics* 69, 709–748.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix Table S1 Country stratification by income.

Appendix Table S2 Westerlund (2007) cointegration test.

Appendix Table S3 KMS (2014) threshold nonlinear model of cross-sectional dependence.