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THE DIFFERENTIAL EFFECTS OF FOREIGN DIRECT INVESTMENT, ENERGY CONSUMPTION AND ECONOMIC GROWTH ON CARBON EMISSIONS: PANEL QUANTILE REGRESSION ESTIMATION

T. LAKSHMANASAMY
Formerly Professor, Department of Econometrics, University of Madras, Chennai
E-mail: tlsamy@yahoo.co.in

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Abstract: This paper estimates the effects of FDI, economic growth and energy consumption on carbon emissions in five ASEAN countries for the period 1981 to 2014. The panel quantile regression estimates show that while the effect of FDI is insignificant, economic growth and energy consumption significantly increase carbon emissions in high-emission ASEAN-5 countries. At higher levels of energy consumption, adoption of green renewable energy and emission control technology mitigate the increase in carbon emissions. The quantile estimates of this paper do not lend support to the U-shaped Environmental Kuznets Curve (EKC) hypothesis. At the same time, the insignificant effect of FDI on carbon emissions does not lend sufficient support to the pollution haven hypothesis in lower-emission ASEAN-5 countries. The negative influence of FDI on carbon emissions at the middle quantiles supports the halo effect hypothesis. The estimated quantile results suggest that uniform carbon emissions control policies are unlikely to succeed equally across low-emissions and high-emissions economies.

Keywords: FDI, energy, growth, emissions, environment, quantile regression.

JEL classification: C23, F43, O13, Q56, R11

Introduction

The increasing manufacturing activities and the associated energy consumption resulting in high carbon emissions, causing global warming and climate change have emerged as one of the most serious problems facing the international community (Wang *et al.* 2014). The accumulation of greenhouse gas (GHG) emissions, most notably the carbon dioxide (CO2) emissions from industries, is the most significant cause for global warming (Zhang *et al.* 2014). Since the industrial revolution, the levels of CO2 emissions from human activities have been continuously increasing and the burning of fossil fuels and deforestation have been identified as the primary cause of increased CO2 concentrations in the atmosphere. In the wake of rapid industrialisation in the post-war era and the rush for economic growth, high demand for energy consumption and the consequent CO2 emissions in a large number of developed and developing countries pose serious problems for development agenda in the post-globalisation strategies. Specifically, carbon emission is the main cause of environmental degradation, a consequence of economic growth.

Though energy consumption caused by economic growth is the decisive factor in environmental pollution, energy consumption and economic growth alone may not explain the whole CO2 emissions. Other factors such as foreign direct investment, a necessary input for economic growth, are also associated with carbon emissions. Invariably, most developing countries vie for attracting FDI as a source of industrialisation and economic growth. Developed countries also encourage shifting of their industries to other countries as a way to reduce energy consumption thereby reducing pollution and developing a green environment in their countries. Therefore, the FDI channel is also encouraged in both developed and developing countries.

Research on the analysis of the relationship between economic growth and energy consumption as well as CO2 emissions and environmental degradation try to establish the causality and estimate the causal effects. Empirical studies use both time series and panel data and apply cointegration techniques including unit root, cointegration, and causality tests. This paper aims to analyse the causal relationship between economic growth, FDI, energy consumption, and CO2 emissions in five ASEAN (Association of Southeast Asian Nations) countries (ASEAN-5) - Indonesia, Malaysia, Philippines, Singapore, and Thailand - the original founding members of ASEAN in 1967 and remain the most influential members of ASEAN in the 21st century. The main objective of this paper is to estimate the impact of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5 economies. Further, this paper examines whether the effects are the same at all levels or vary across the emission distribution i.e. differential effects with the most and least emissions.

In terms of per capita income, Singapore (US$ 34,758) ranked the highest, followed by Malaysia (US$ 6318), Thailand (US$ 3163), Indonesia (US$ 1570) and Philippines (US$ 1403). The average annual economic growth rate in ASEAN economies has been above 5 percent between 2000 to 2013, far exceeding the OECD average growth (1.6 percent) and comparable to the growth experienced by India (7.2 percent) and Africa (4.8 percent). Figure 1 presents the time series of GDP per capita for the ASEAN-5 countries. Overall, a persistent growth of GDP per capita level is observed in all ASEAN-5 countries, though Singapore stands atop.

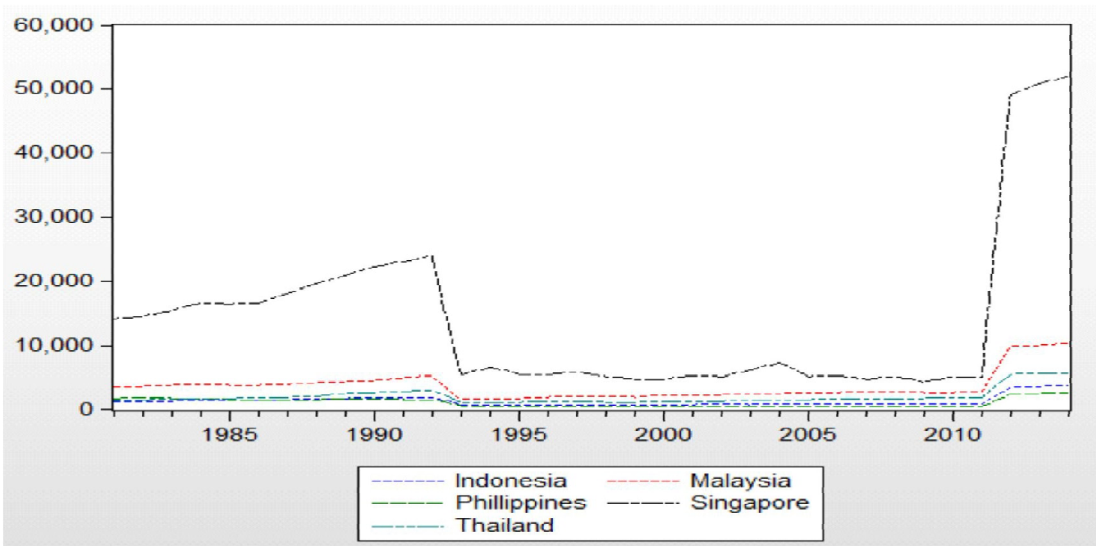

Figure 1: GDP per capita in ASEAN-5 Countries (in constant 2010 US$)

Figure 2 depicts the time series of FDI for the ASEAN-5countries. The FDI inflow in Singapore is not only higher but also has been increasing faster than that in the other four countries ASEAN economies where there has been only a slight increase in the FDI inflows over the years.

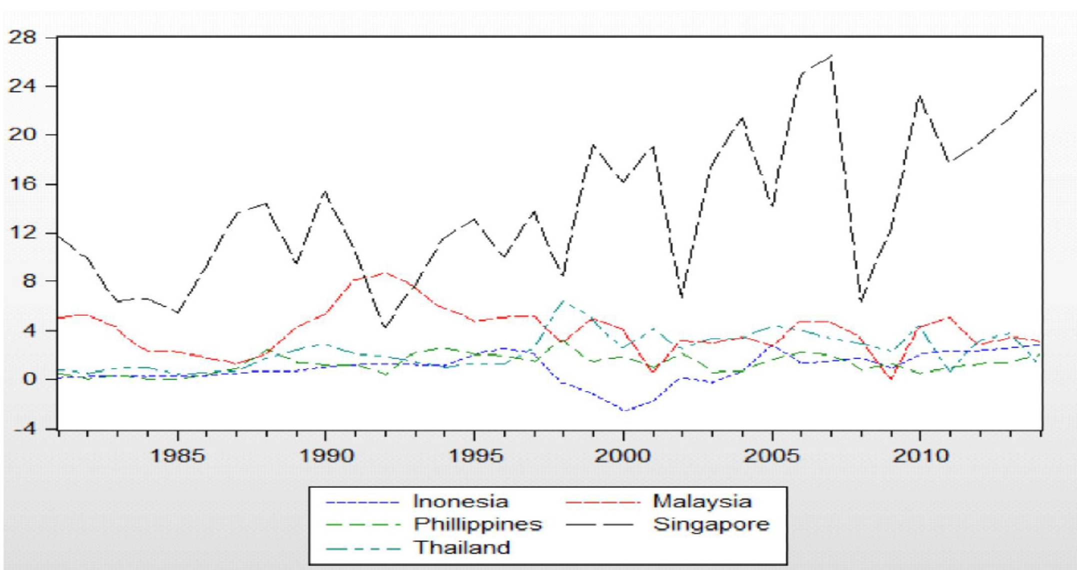

Figure 2: FDI Inflow in ASEAN-5 Countries (share of net FDI inflow in GDP)

Figure 3 presents the time series of energy consumption of the ASEAN-5 countries. All five countries show an increasing trend of energy consumption over the years. However, since 1994, Singapore shows a unique feature with regard to energy consumption. Since 1994, the level of energy consumption in Singapore has been declining in the face of the continuous increase in economic growth. Further, the energy consumption in Malaysia and Thailand are steadily growing, the same in Indonesia and the Philippines do not show any increasing trend.

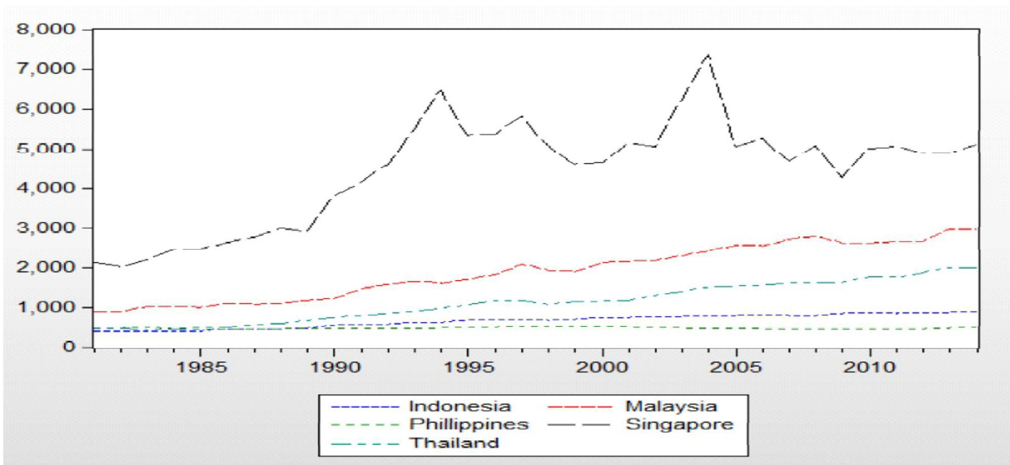

Figure 3: Energy Consumption in ASEAN-5 Countries (kg of oil equivalents)

Figure 4 depicts the trend in carbon emissions in ASEAN-5 countries. The carbon emissions closely follow the trends in energy consumption in these economies. In Singapore, there has been a persistent decrease since 1997 in carbon emissions. A persistent increase in the emissions level can be observed in the other four countries.

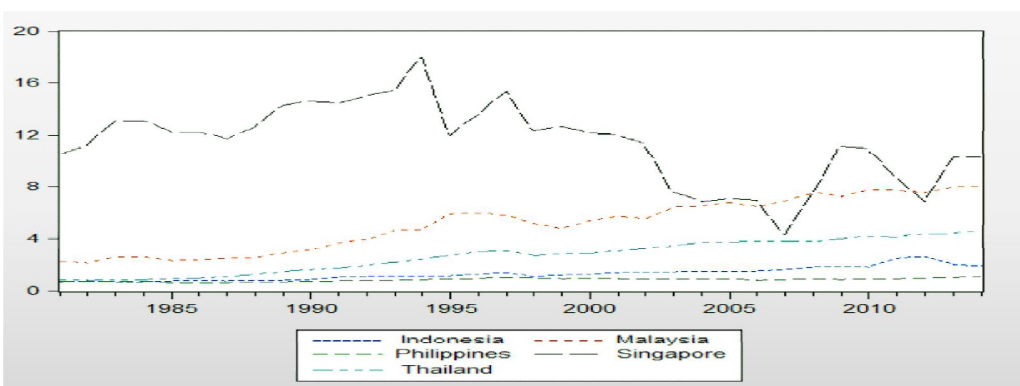

Figure 4: Carbon Emissions in ASEAN-5 Countries (metric tons per capita)

Thus, compared with the other ASEAN countries, Singapore stands atop with high GDP per capita, FDI inflow and energy consumption, but declining trends in carbon emissions and energy consumption. Singapore is a developed country and follows improved energy usage efficiency. Thus, Singapore shows the Environmental Kuznets Curve hypothesis i.e. an inverted U-shaped relationship between environmental pollution and income. As the other four ASEAN-5 countries are developing countries, there is increasing trends in economic growth, energy consumption and carbon emissions.

Review of Literature

Perman and Stern (2003)examine the U-shaped relation between various indicators of environmental degradation such as sulfur emissions and income per capita for 74 countries over a span of 31 years. The cointegration test indicates no cointegration relationship between environmental degradation and income.

Hassain (2011) examines the dynamic causal relationships between carbon dioxide emissions, energy consumption, economic growth, trade openness and urbanisation for a panel of newly industrialised countries (NIC) for the period 1971-2007. The four different panel unit root tests show that all panel variables are integrated of order one and the Johansen Fisher panel cointegration test show that there is a cointegration vector among the variables. The Granger causality test shows no evidence of a long-run causal relationship, but there is a unidirectional short-run causal relationship from economic growth and trade openness to carbon dioxide emissions, from economic growth to energy consumption, from trade openness to economic growth, from urbanisation to economic growth and from trade openness to urbanisation. The results show that the long-run elasticity of carbon dioxide emissions with respect to energy consumption (1.22) is higher than the short-run elasticity of (0.60). This indicates that over time high energy consumption in the newly industrialised countries gives rise to more carbon dioxide emissions and the environment gets polluted more.

Arouri *et al.* (2012) investigate the relationship between carbon dioxide (CO2) emissions, energy consumption and real GDP for 12 middle-east and African (MANA) countries for the period 1981-2005. The panel unit roots test show that the MENA countries are cross-sectionally correlated and the cointegration results show a long-term relationship between CO2 emissions and potential determinants. The error correction model (ECM) results also show evidence of positive causality from energy consumption to CO2 emissions. Further, the causality from GDP to CO2 emissions depends on the level of economic growth and the real GDP exhibits a quadratic relationship with CO2 emissions satisfying the environment Kuznets curve (EKC) hypothesis in a majority of the MANA countries.

Zhang and Lin (2012) investigate the impact of economic indicators on pollution (CO2 emissions) in China during the period 1995-2010 using panel fixed effects model. They use demographic intensity, urbanisation, GDP, industrial production, production of services and energy consumption as economic indicators. The results show that demographic intensity, GDP, industrial production, and energy consumption have an impact on CO2 emissions.

Omri (2013) study the impact of economic activity on environmental degradation in the middle-east and African (MANA) countries for the period 1990-2011. He utilizes CO2 emissions as an indicator of pollution and labour, capital, population, financial development, and GDP as indicators of economic activities. The regression results lend support for the presence of a positive and significant impact of the GDP and negative impact of financial development and capital on CO2 emissions.

Rafindadi *et al.* (2014) study the causal relationship between pollution and economic activity in Asia-Pacific countries for the period 1975-2012employing panel fixed effects estimation method. In this study, pollution is measured by CO2 emissions and economic indicators are the GDP, water, added value of natural resources and energy consumption. The estimated results show the existence of a positive and significant relationship between CO2 emissions and GDP. And also energy consumption affects pollution positively.

Data and Methodology

In order to examine the determinants of carbon emissions in the ASEAN-5 countries - Indonesia, Malaysia, Philippines, Singapore and Thailand - this paper uses a panel of annual data for 34 years for these five ASEAN economies on FDI, economic growth, energy consumption and carbon emissions in these economies for the period 1981 to 2014. The data are collected from the 2015 World Development Indicators of the World Bank. All the variables used are transformed into natural logarithms to reduce to effect of heteroscedasticity. Table 1 presents the description and measurement of the variables used in the empirical analysis.

Table 1: Description of the Variables used in the Carbon Emissions Analysis

Variable	*Description and measurement*
CO2	Carbon dioxide emissions (metric tons per capita)
ENC	Energy consumption (kg of oil equivalent per capita)
GDPpc	Economic growth - GDP per capita US$ at 2010 constant prices)
POP	Population of the country
TROPEN	Trade openness (% of GDP)
FDI	Foreign direct investment - net inflows (% of GDP)
FINDEV	Financial development - domestic credit to the private sector(% of GDP)

Source: World Bank (2015): World Bank Indicators, 2015.

Empirically, as the data are time series, a prerequisite is to test for stationarity to determine if the data series is stationary or not. The panel cointegration is to examine the long-run and short-run relationship between the variables. The dynamic relationship among the variables is analysed by a panel quantile regression method to understand the differential effects at different quantiles of the carbon emissions distribution. The panel-based unit root tests for the stationarity of the series are those of Quah (1994), Breitung (2000), Breitung and Mayer (1994), Levin, Lin and Chu (2002), Im, Pesaran and Shin (2003),Fisher-type tests using ADF and PP tests (Phillips and Perron, 1988; Maddala and Wu, 1999; Hadri, 2000; Choi, 2001).

Panel Data Method

A panel unit root test is based on the following univariate regression:

$$\Delta y_{it} = \rho_i y_{it-1} + \delta x_{it} + u_{it} \; i = 1,\ldots, N \; t = 1,\ldots, T \tag{1}$$

where x_{it} are the exogenous variables in the model including any fixed effects or individual trends, ρ_i are the autoregressive coefficients and the errors u_{it} are assumed to be a mutually independent idiosyncratic disturbance. If $|\rho_i|<1$, y_i is said to be weakly (trend) stationary. On the other hand, if $|\rho_i| = 1$, then yicontains a unit root.

Augmented Dickey-Fuller Unit Root Test: The ADF test is based on the following univariate regression:

$$\Delta y_{it} = \rho_i y_{it-1} + \sum_{k=1}^{p_i} \gamma_{ik} \Delta y_{it-k} + \delta_i x_{it} + u_{it} \tag{2}$$

Assuming a common $\alpha = \rho-1$ and allowing the lag order p_i for the difference termsto vary across cross-sections, the null and alternative hypotheses for the test unit root test are specified as:

Null hypothesis: H_0: $\alpha = 0$ (presence of unit root)

Alternative hypothesis: H_1: $\alpha < 0$ (no unit root)

However, the individual unit root tests have limited power as there may be too many unit roots in panel data.

Levin-Lin-Chu Test: The Levin-Lin-Chu Test (LLC) suggests the following hypotheses:

Null hypothesis: H_0: each time series contains a unit root

Alternative hypothesis: H_1: each time series is stationary

where the lag order p is permitted to vary across individuals. The procedure is to first run the Augmented Dickey-Fuller (ADF) unit root test for each cross-section on the equation (2). Then, run two auxiliary regressions:

Δy_{it} on Δy_{it-k} and x_{it} to obtain the residuals $\hat{e}_{it}$ (3)

$y_{i,t-1}$ on $\Delta y_{it-k} x_{it}$ to obtain the residuals $\hat{v}_{it-1}$ (4)

The next step is to standardise the as:

$$\tilde{e}_{it} = \hat{e}_{it}/\hat{\sigma}_{ui} \tag{5}$$

$$\tilde{v}_{it-1} = \hat{v}_{it}/\hat{\sigma}_{ui} \tag{6}$$

where σ_{ui} denotes the standard error from each ADF. The final step is to run the pooled OLS regression:

$$\tilde{e}_{it} = \rho\tilde{v}_{it-1} + \hat{u}_{it} \tag{7}$$

The Levin-Lin-Chu null hypothesis for panel unit root test is: H_0: $\rho = 0$.

Breitung test: In the Breitung panel unit root test, only the autoregressive portion, not the deterministic terms, are included in the Levin-Lin-Chu test procedure. Applying forward orthogonalisation transformation i.e. subtracting the mean of the future observations from each of the first T-1 observations ($\tilde{y}$), to the residuals $\hat{e}_{it}$, the transformed residuals are obtained as:

$$e^*_{it} = \rho v^*_{it-1} + u^*_{it} \tag{8}$$

Then, the pooled regression is estimated as:

$$\Delta y^*_{it} = \sqrt{\frac{T-t}{T-t+1}}\left(\Delta\tilde{y}_{it} - \frac{\Delta\tilde{y}_{it-1} + \cdots + \Delta\tilde{y}_{iT}}{T-t}\right) = \alpha y^*_{it-1} + \varepsilon_{it} \tag{9}$$

Then test for the significance of α.

Im-Pesaran-Shin (IPS) test: The Im, Pesaran and Shin panel unit root test specifies a separate ADF regression for each cross-section and the hypotheses are specified as:

Null hypothesis: H_0: $\alpha = 0$, for all i

$$\text{Alternative hypothesis: } H_1: \begin{cases} \alpha_i = 0 & for\ i = 1, \dots, N_1 \\ \alpha_i < 0 & for\ i = N_1 + 1, \dots, N \end{cases} \tag{10}$$

Fisher-ADF and Fisher-Phillips-Perron tests: The Fisher-type test uses p-values from unit root tests for each cross-section i. The Fisher is as follows:

$$P = -2\sum_{i=1}^{N} lnp_i \tag{11}$$

The next step is to test for the existence of a long-run cointegration among CO2 and other variables using panel cointegration tests. The panel cointegration tests are based on the following panel regression model:

$$y_{it} = \alpha_i + \delta_i t + \beta_{mi}x_{mit} + e_{it} i = 1, \dots, N;\ t = 1, \dots, T;\ m = 1, \dots, M \tag{12}$$

where i represents the cross-section units, t the time and m the number of regressors. In this setup, α is the individual specific intercept or fixed effects parameter which varies across individual cross-sectional units and δ_i is individual specific time effects. The residual-based panel cointegration test of Pedroni (1999; 2004) uses the first difference of the panel regression:

$$\Delta y_{it} = \beta_{mi}\Delta x_{mit} + \eta_{it} \tag{13}$$

The long-run variance of the estimated residuals from the first differenced panel regression is computed as:

$$\hat{\psi}^2_{it} = \frac{1}{T}\sum_{t=1}^{T}\hat{\eta}^2_{it} + \frac{2}{T}\sum_{k=1}^{p_i}\left(1 - \frac{k}{p_i+1}\right)\sum_{t=k+1}^{T}\hat{\eta}_{it}\hat{\eta}_{it-k} \tag{14}$$

The panel-ρ and group-ρ statistics are obtained from the panel regression residuals from equation (12):

$$\hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \hat{\mu}_{it} \quad (15)$$

The long-run variance ($\hat{\sigma}_i^2$) and the contemporaneous variance ($\hat{s}_i^2$) of $\hat{\mu}_{it}$ are then computed as:

$$\hat{\sigma}_i^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{\mu}_{it} \quad (16)$$

$$\hat{s}_i^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{\mu}_{it} + \frac{2}{T}\sum_{k=1}^{p_i}\left(1 - \frac{k}{p_i+1}\right)\sum_{t=k+1}^{T} \hat{\mu}_{it}\hat{\mu}_{it-k} \quad (17)$$

Then, compute λ_i as:

$$\lambda_i = \frac{1}{2}(\hat{\sigma}_i^2 - \hat{s}_i^2) \quad (18)$$

The panel-*t* and group-*t* statistics are again computed from the panel regression residuals from equation (12):

$$\hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \sum_{k=1}^{p_i} \hat{\rho}_{ik} \Delta\hat{e}_{it-k} + \hat{\mu}_{it}^* \quad (19)$$

The variance of ($\hat{\mu}_{it}^*$) is computed as:

$$\hat{s}_i^{*2} = \frac{1}{T}\sum_{t=1}^{T} \hat{\mu}_{it}^{*2} \text{ and } \tilde{s}_{NT}^{*2} \equiv \frac{1}{N}\sum_{i=1}^{N} \hat{s}_i^{*2} \quad (20)$$

Pedroni (1999; 2004) computes the panel cointegration statistics from panel-ρ, panel-*t*, group-ρ and group-t statistics and show that the test statistics are standard normally distributed. Then, the null hypothesis of no cointegration for the panel cointegration test is the same for each statistic:

Null hypothesis: H_0: $\rho_i = 1 \; \forall i$

However, there is a difference in the alternative hypothesis for the between-dimension-based and within-dimension based panel cointegration tests. The between-dimension based statistics does not require a common value of ρ:

Alternative hypothesis: H_1: $\rho_i < 1 \; \forall i$

The within-dimension-based statistics requires a common value for $\rho_i = \rho$:

Alternative hypothesis: $\rho_i = \rho < 1 \; \forall i$

Under the alternative hypothesis, all the panel cointegration test statistics diverge to negative infinity. Thus, the left tail of the standard normal distribution is used to reject the null hypothesis.

Panel Quantile Regression Method

To estimate the differential effects at different points of the distribution function, the quantile regression method, proposed by Koenker and Bassett (1978), is used. The quantile regression is a generalisation of median regression analysis to other quantiles of the distribution function and is robust to outliers and heavy distributions. The conditional quantile of yigiven xi is as follows:

$$Q_{yi}(\tau|x_i) = \beta_\tau x_i^\tau \tag{21}$$

The unobserved heterogeneity is controlled by the fixed effects panel quantile regression, which estimates the conditional heterogeneous covariance effects of carbon emissions drivers. The fixed effects panel quantile regression is specified as:

$$Q_{yit}(\tau_k|\alpha_i, x_{it}) = \alpha_i + \beta_{\tau_k} x_i^\tau \tag{22}$$

where *k* indicates the quantiles. However, the fixed effects panel quantile regression has a drawback of the incidental parameters problem with the inclusion of a considerable amount of fixed effects (α_i) and the estimates are inconsistent with large cross-sections and less time period (Lancaster, 2000). Moreover, the fixed effects panel quantile regression method to eliminate the observed fixed effects relying on the basis of linear operators is unfeasible in the conditional quantile regression method (Canay, 2011). To overcome these problems, Koenker (2004) proposes a joint estimation of the unobservable fixed effect as parameters along with the covariate effects for different quantiles. This method imposes a penalty on the minimisation to address the computational problem of estimating a mass of parameters specifically. The parameter estimate is calculated as follows:

$$\underset{\alpha, \beta}{Min} \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{k=1}^{K} \omega_k \rho_{\tau_k} \left[y_{it} - \alpha_i - \beta_{\tau_k} x_i^\tau \right] + \lambda \sum_{i=1}^{N} |\alpha_i \tag{23}$$

where ρ_{τ_k} is the quantile loss function, ω_k is the relative weight given to the k-th quantile that controls for the contribution of the *k*-th quantile on the estimation of the fixed effects, λ is the tuning parameter that reduces the individual effects to zero to improve the performance of the estimate of β. If λ term goes to zero, then the penalty term disappears, and the usual fixed effects estimator is the result. However, if the λ term goes to infinity, then the model is estimated without individual effects. Alexander *et al.* (2011) and Lamarche (2010; 2011) propose equally weighted quantiles $\omega_k = 1/K$. The estimating empirical panel conditional quantile function for τ^{th} quantile is specified as:

$$\begin{aligned} Q_{CO_{2_{it}}}(\tau_k|\alpha_i, \gamma_t, x_{it}) &= \alpha_i + \gamma_t + \beta_{1\tau} FDI_{it} + \beta_{2\tau} GDPpc_{it} + \beta_{3\tau} ENC_{it} + \\ &\beta_{4\tau} TROPEN_{it} + \beta_{5\tau} FINDEV + \beta_{6\tau} POP_{it_{it}} + \varepsilon_{it} \end{aligned} \tag{23}$$

where the carbon dioxide emissions indicator is estimated as a function of energy consumption, foreign direct investment and economic growth along with other control variables.

Empirical Analysis

Table 2 presents the descriptive statistics of the variables used to estimate the effects of FDI, economic growth and energy consumption on carbon emissions in the ASEAN-5 economies. The distributions of all of the variables are skewed, and the kurtosis values show that the seven series distributions are more concentrated with longer tails. The Jarque-Bera tests strongly reject the null hypothesis of normality, indicating the non-normality of the unconditional distribution of all the variables.

Table 2: Descriptive Statistics of Variables

Variable	*Description*	*Mean*@	*Median*#	*Jarque-Bera*
CO_2	Carbon dioxide (CO_2) emissions from consumption of oil, gas and coal based on standard global average conversion factors (metric tons per capita)	4.250 (4.261)	2.461 [1.257] (3.503)	46.578***
GDPpc	Gross domestic product real per capita (constant 2010 US$)	4338.417 (7738.343)	1719.264 [4.266] (23.901)	3610.083***
FDI	Foreign direct investment of cross-border investment made by a resident in one economy (net inflows) (% of GDP US$)	4.488 (5.692)	2.403 [1.999] (6.538)	201.958***
ENC	Energy consumption of commercially traded fuels including modern renewable used to generate electricity (kg of oil equivalent per capita)	1711.155 (387.097)	1003.582 [1.454] (4.121)	68.771***
FINDEV	Financial development measured by domestic credit to the private sector (% of GDP US$)	72.306 (40.290)	77.802 [0.219] (1.931)	9.448***
TROPEN	Trade openness of removal or reduction of tariff obstacles such as duties and surcharges, and nontariff obstacles such as licensing rules, quotas and other requirements (% of GDP US$)	175.623 (439.987)	92.247 [10.083] (116.005)	9333.501***
POP	Total population of the country within the scope of census	29117845 (55266094)	1126233 [2.331] (7.951)	327.651
Obs.		170		

Note: *** Significant at 1 percent level. @ standard deviations in parentheses. # Skewness in brackets and kurtosis in parentheses.

Table 3 presents the results of the panel unit root tests. The panel unit root test results indicate that the null hypothesis of the existence of a unit root could not be rejected for all variables at the levels, except the FDI. However, the unit root null hypothesis for all variables at the first difference could be completely rejected at 1 percent level of significance. Therefore, an empirical analysis that uses the first difference sequence is necessary. As the results of the panel unit root tests indicate that the variables contain a panel unit root, the

Johansen Fisher panel cointegration test is used to examine whether there is a long-run relationship among the variables. The Johansen panel cointegration test results presented in Table 4 indicate the existence of cointegrating vectors using one lag length.

Table 3: Panel Unit Root Tests

Variable	*Levin-Lin-Chu*	*Breitung*	*Im- Pesaran-Shin*	*Fisher-Augmented Dicky-Fuller*	*Fisher-Phillips-Perron*
At level					
CO_2	0.020	-1.844	-1.317	15.738	11.450
GDPpc	5.779	3.636	4.543	0.206	0.292
FDI	-0.898***	-3.257	-2.626	25.260	37.140***
ENC	0.234	-1.089	-0.259	11.468	13.121
FINDEV	-0.084	-1.404	0.312	6.654	4.058
TROPEN	-6.945	-7.580	-4.572	37.750	81.197
POP	4.967	2.948	4.288	0.246	0.337
At first difference					
CO_2	-5.182***	-4.212***	-6.255***	54.195***	84.350***
GDPpc	-7.181***	-2.496***	-5.105***	42.287***	84.864***
FDI	-3.685***	-6.181***	-8.418***	75.121***	61.104***
ENC	-5.103***	-4.833***	-5.994***	51.110***	12..701***
FINDEV	-1.467***	-5.454***	-3.410***	28.868***	48.424***
TROPEN	-11.860***	-14.320***	-11.002***	98.714***	13.170***
POP	-7.242***	-3.020***	-5.184***	42.985***	84.306***

Note: *** Significant at 1 percent level.

Table 4: Johansen Panel Cointegration Test

Hypothesised no. Of CEs	*Trace value*	*Prob.*	*Max-Eigen value*	*Prob.*
None	97.05***	0.0000	52.86***	0.0000
At most 1	49.78***	0.0000	42.58***	0.0000
At most 2	19.27***	0.0370	14.09	0.1691
At most 3	10.02	0.4390	5.880	0.8252
At most 4	7.452	0.6822	8.278	0.6017
At most 5	4.693	0.9107	5.061	0.8870
At most 6	6.442	0.7769	6.442	0.7769

Note: *** Significant at 1 percent level.

To facilitate comparisons, the carbon emission model is first estimated by the OLS pooled regression and fixed effects regression methods and the estimated results are presented in Table 5. The fixed effects model controls for the time specific and spatially invariant variables, whose omission could bias the estimates in the typical time series OLS estimation. The fixed effects estimates show that GDP has a positive and significant effect on carbon emissions. Similarly, energy consumption is positively related to carbon emissions. These two results together imply that economic growth necessitates environmental degradation. The effects of FDI and domestic investments on carbon emissions are insignificantly negative. The estimated relationship between FDI and pollution support the effect hypothesis and provide no evidence for the FDI's deteriorating impact on environmental. However, these estimated average effects do not provide a more complete picture of the influence at different points of the distribution of carbon emissions. Therefore, panel quantile regression is to be estimated to understand the heterogeneous effects across the different percentiles in the conditional distribution of carbon emissions.

Table 5: Pooled Regression and Panel Fixed Effects Estimates of Carbon Emissions

Dependent variable: Carbon emissions

Variable	*OLS pooled regression*	*OLS fixed effects*
lnGDPpc	0.456***(6.22)	0.524*** (6.66)
lnFDI	-0.020 (0.88)	-0.011(0.51)
lnENC	0.526*** (6.35)	0.414*** (4.83)
lnTROPN	0.045 (1.23)	0.052 (1.36)
lnFINDEV	0.217*** (5.39)	0.090 (1.33)
lnPOP	-0.034*** (5.07)	-0.043*** (6.15)
Constant	-7.066*** (31.59)	-6.253*** (13.08)

Note: Absolute t-values in parentheses. *** Significant at 1 percent level ** Significant at 5 percent level.

Table 6 presents the estimated results of the panel quantile regression. The estimated quantile coefficients of lnGDPpc are highly significant and have a positive sign at all quantiles. The effect of economic growth increases on carbon emission increases with every quantile from 2 percent at 10^{th} quantile to 7 percent at the 95^{th} quantile. Similarly, the coefficients of lnENC are also highly significant at all quantiles and the effect on carbon emissions is consistently positive, but slightly decreases over the quantiles from 5 percent at the 10^{th} quantile to 4 percent at the 95^{th} quantile. Both these results together imply that as the economy grows energy consumption increases which cause more carbon emissions. At the higher levels of energy consumption, a tilt towards renewable sources of energy and better technology use for emission control are adopted and hence low carbon emissions. A higher economic growth level can mitigate the increase in carbon emissions in high-emissions countries. Thus, the quantile regression results of the relationship between economic growth and environment observed in the ASEAN-5 economies does not lend support for the U-shaped Environmental Kuznets Curve (EKC) hypothesis.

Table 6: Panel Quantile Regression Estimates of Carbon Emissions

Dependent variable: Carbon emissions							
Variable	*10th*	*30th*	*40th*	*50th*	*70th*	*90th*	*95th*
lnGDPpc	0.19*	0.51***	0.59***	0.61***	0.65	0.71***	0.71***
	(1.80)	(3.27)	(5.38)	(6.50)	(0.08)	(11.11)	(11.65)
lnFDI	0.009	-0.003	-0.007	-0.006	-0.009	-0.007	0.01
	(0.32)	(0.15)	(0.49)	(0.44)	(0.66)	(0.45)	(1.13)
lnENC	0.56***	0.55***	0.52***	0.51***	0.47	0.45***	0.48***
	(3.96)	(3.49)	(4.88)	(5.70)	(0.08)	(5.24)	(5.37)
lnTROPN	0.02	0.02	-0.002	0.006	0.01	0.03	0.002
	(0.61)	(0.67)	(0.08)	(0.20)	(0.02)	(0.89)	(0.14)
lnFINDEV	0.39***	0.22***	0.19***	0.16***	0.13	0.07*	0.02
	(6.74)	(6.89)	(7.55)	(7.10)	(0.02)	(1.96)	(0.38)
lnPOP	-0.02**	-0.04***	-0.04***	-0.04	-0.05	-0.05***	-0.06***
	(2.05)	(3.28)	(5.25)	(0.007)	(0.005)	(11.11)	(11.37)
Constant	-6.37***	-7.51***	-7.64***	-7.56***	-7.50***	-7.44***	-7.30***
	(19.51)	(53.25)	(56.97)	(54.44)	(50.97)	(35.08)	(33.35)

Note: Absolute t-values in parentheses. *** Significant at 1 percent level ** Significant at 5 percent level.

The impact of FDI on carbon emissions is statistically insignificant at all the quantiles. Probably at the lower quantiles, FDI is insufficient to support the pollution haven hypothesis in the low-emissions countries and at the higher quantiles, the influence of FDI on carbon emissions is negated by the global standards. These results support the halo-effect hypothesis in high-emission countries. Also, the insignificant impact of FDI at lower quantiles mean that most FDI likely investments in non-polluting sectors of low-emissions countries. In high-emissions environments, the FDI inflow may develop technology and innovations in production methods mostly by multinational companies. These more advanced technologies tend to disseminate cleaner technology that will be less harmful to the environment and such technologies may also be indirectly passed on to domestic firms via backward or forward linkages. Therefore, in high-emissions countries, an increase in FDI improves the regions environmental quality. The results show that effect hypothesis is valid in high-emissions ASEAN-5countries.

The other results are also informative. The impact of the population size on carbon emissions is significantly negative both at lower quantiles and at higher quantiles; at the median quantile, population becomes insignificant. These results imply that a larger population size leads to higher carbon emissions in low-emissions countries whereas the opposite holds true in high-emissions countries. The effect of financial development, similar to economic growth, is positive at all quantiles. The coefficients of private sector investments are significant at lower quantiles but become insignificant at higher quantiles. Moreover, the effects of financial investments on carbon emissions decrease from 4 percent at the lower quantile to almost zero percent at the 95th quantile, again confirming the concern for environmental quality at higher development levels. Trade openness has no significant effect on carbon emissions in the ASEAN-5 economies.

In order to examine the significance of the heterogeneity of the parameters across quantiles of the panel quantile regression model, the inter-quantile tests are performed. The Wald tests are used to check for slope equality across quantiles. The variance-covariance matrix of the corresponding coefficients is obtained from the bootstrap procedure. Table 7 and Figure 5 present the results of the test of equality of the coefficients between the lower quantiles and the upper quantiles. The test is whether the slope coefficient at the 10th quantile is the same as that in the middle quantile (50th quantile) and the higher quantiles (95th quantile). The tests reject the hypothesis of parameter homogeneity except in the cases of energy consumption. Thus, there is a differential effect of FDI, economic growth, financial development and population on the distribution of carbon emissions in ASEAN-5 countries.

Table 7: Wald Test for Equality of Slope Parameters at Quantiles

Variable	*10thquantile vs 50th quantile*		*10th quantile vs 95th quantile*	
	Test statistic	*p-value*	*Test statistic*	*p-value*
lnGDPpc	0.053	0.166	8.707***	0.051
lnFDI	1.009**	0.026	3.018*	0.016
lnENC	6.644	0.182	0.482	0.090
lnTROPN	8.046**	0.034	0.003***	0.020
lnFINDEV	3.429**	0.056	1.0154**	0.041
lnPOP	5.007	0.012	8.057**	0.004

Note: ** Significant at 5 percent level.

Conclusion

The main objective of this paper is to estimate the effect of FDI, economic growth and energy consumption on carbon emissions in five ASEAN (Association of Southeast Asian Nations - Indonesia, Malaysia, Philippines, Singapore, and Thailand) countries. The paper used a panel data from the five ASEAN-5 counties for the period 1981 to 2014 and applied the panel quantile regression method to understand the differential effects of the factors on carbon emissions at different quantiles of the distribution. The estimated empirical results show that the impacts of various factors on carbon emission in ASEAN-5 economies are evidently heterogeneous. The quantile results are further confirmed by the Wald test that supports the observed differences along the estimated coefficients are significant across quantiles. Economic growth and energy consumption significantly increases carbon emissions in high-emission ASEAN countries. However, at higher levels of energy consumption, adoption of green renewable energy and emission control technology

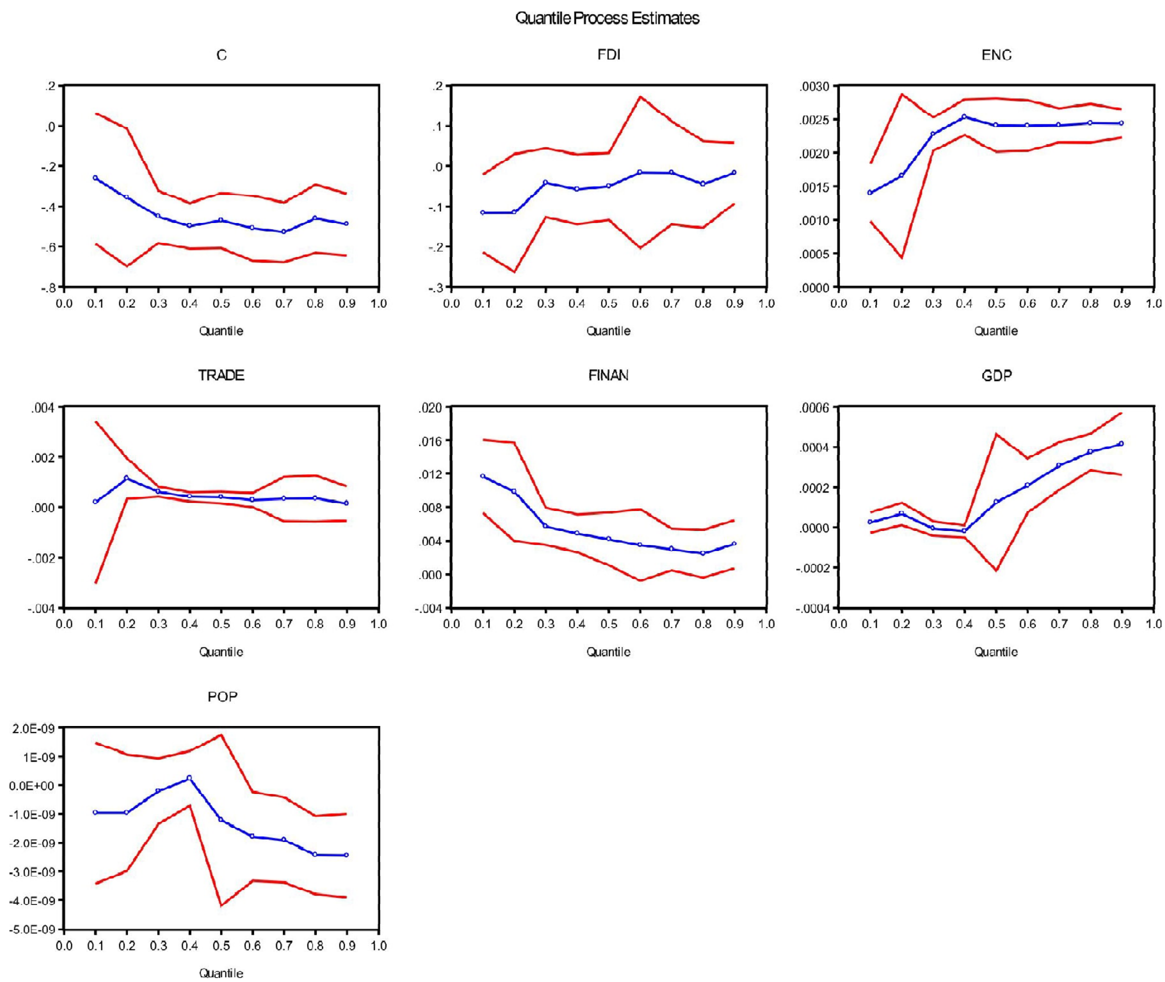

Figure 5: Heterogeneity in Panel Quantile Regression Estimates

mitigate the increase in carbon emissions. The quantile estimates of this paper do not lend support to the U-shaped Environmental Kuznets Curve (EKC) hypothesis.

At the same time, the insignificant effect of FDI on carbon emissions also does not lend sufficient support to the pollution haven hypothesis in lower-emission ASEAN countries. However, the negative influence of FDI on carbon emissions at the middle quantiles supports the halo effect hypothesis. An increase in FDI may improve the regions environmental quality. In addition, high financial development which indicates private investments increases carbon emissions trade openness has no influence on carbon emissions in ASEAN-5 economies. Therefore, uniform carbon emissions control policies are unlikely to succeed equally across countries with different carbon emissions levels.

Therefore, carbon emissions control measures should be tailored differently across low-emissions and high-emissions economies.

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