Thailand Econometrics Society, Vol. 3, No. 3 (January 2011), 258 - 267

The impact of population on CO2 emissions: Provincial panel evidence from Thailand

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ARTICLE INFO

Keywords:
CO2 Emissions, Panel Data, Tobit model, Random Parameters Panel Data models, Simulation estimator, General Method Moment, Panel Unit root, Panel Co-integration

ABSTRACT

This paper analyses the impact of population growth on CO_2 emissions at the provincial level in Thailand. Past researchers have assumed a unitary elasticity of emissions with respect to population growth. In the classical and random-parameters panel data models estimated by a simulation estimator, population does not explain and moves in the opposite direction from CO_2 emissions. However, the Tobit panel data estimator shows that population is significant and moves in the same direction as CO_2 emissions. Nonetheless, the Tobit estimator does not show a unitary elasticity of emissions. The sample covers the period 2001- 2008 for each of the 76 Thai provinces.

1. Introduction

It is generally agreed that many types of modern economic activity have been harmful to the environment. Population increases have led to increased energy consumption in the form of fossil fuels, coal and wood-burning; and, consequently, to greater atmospheric pollution. The demographic factor would therefore seem to explain a large portion of the the sources of air pollution. Nonetheless, Cramer (1998, 2002) and Cramer and Cheney (2000)'s evaluations of the effects of population growth on air pollution found a positive relation only for some sources of emissions but not others. Dietz and Rosa (1997) and York *et al.* (2003) studied the impact of population on carbon dioxide emissions and energy use within the framework of the IPAT[1] (Impact-Population-Affluence-Technology) model. The results from these studies indicate unity elasticity of CO_2 emissions and energy with respect to population. Shi (2003) and Cole and Neumayer (2004) found a positive link between CO_2 emissions and a set of explanatory variables including population, the urbanization rate, affluence, and technology. Some research also outlined the negative environmental impacts caused by demographic pressure (Daily and Ehrlich, 1992; Zaba and Clarke, 1994), but they failed to analyse this impact within an appropriate quantitative framework.

In the last two decades, the relationship between energy use and income is a widely studied topic in the field of energy economics. In the late seventies, Kraft and Kraft (1978) found evidence in favour of causality running from GDP to energy consumption. Yu and Hwang, 1984; Yu and Choi, 1985 are also studies showing that the causality runs in the opposite direction: from energy consumption to GDP (e.g. Lee, 2005). Decomposition methods have been applied to an increasing number of pollutants in developed and developing countries (e.g. Hamilton and Turton, 2002; Bruvoll and Medin, 2003; Lise, 2005). Hamilton and

Turton (2002) concluded that income per capita and population growth are the main two factors increasing carbon emissions in OECD countries, whereas the decrease in energy intensity is the main factor reducing them.

The environmental Kuznets curve (EKC) takes emissions per capita for different pollutants as an endogenous variable, assuming implicitly that the emission-population elasticity is unitary (e.g. Cole *et al.*, 1997; Panayotou *et al.*, 2000). However, the non-appropriated techniques and the presence of omitted variables bias are taken into account in the selection of the proper techniques. The results show that the EKC does not exist (Perman and Stern, 2003). Cole *et al.* (1997) and Suri and Chapman (1998) found that energy use per capita increases monotonically with income per capita.

The aim of this paper is to analyse the impact of population growth on CO2 emissions in the 76 province of Thailand using an econometric model to decompose emissions into the scale, composition and technique effects described above. We take into account dynamic effects, the time series properties of the data and the presence of heterogeneity in the sample. We specify a model in which CO_2 emissions are related with the level of income per capita and the population size and the energy intensity of each of the 76 provinces in Thailand.

2. Theoretical Framework

Ehrlich and Holdren (1971) suggested a suitable framework to analyse the determinants of environmental impact known as the IPAT equation: *I=PAT*. In this equation, I represents environmental impact, *P* is the population size, A is affluence or wealth, and *T* denotes the level of environmentally damaging technology. In this paper, the IPAT model can be expressed as an identity where *A* could be defined as consumption per capita and *T* as pollution per unit of consumption. As stated by MacKellar et al. (1995), the IPAT identity is a suggestive approach that shows clarifies to what extent environmental impact cannot be reduced to a single factor. The initial specification is given by the following equation:

$$I_i = \alpha P_i^{\beta} A_i^{\gamma} T_i^{\delta} e_i \qquad (1)$$

where I_i, P_i, A_i and T_i are the variables defined above; α, β, γ and δ are parameters to be estimated and e_i is the random error.

The estimator

Because much of the past literature suffers from misspecification errors, we shall endeavour to estimate and verify the coefficients for a sample of panel data under six distinct models: the Tobit, random-parameters panel data, simulation estimator, general method of moments, panel unit root, and panel co-integration models.

Fixed effect models estimated with this IPAT are 'one way' or 'one factor' designs of the form

$$y_{it} = \alpha + \beta x + \varepsilon$$

where ε_{it} is a classical disturbance with E[ε_{it}]=0 and Var[ε_{it}]= σ_{ε}^2 .In the fixed effects model, u_i is a separate constant term for each unit.

$$y_{it} = \alpha + \beta x + \varepsilon \;.$$

$$E[\varepsilon_{it}|X_i] = 0, Var[\varepsilon_{it}|X_i] = \sigma^2,$$

$$Cov\left[\varepsilon_{it}, \varepsilon_{js} \middle| X_i, X_j\right] = 0 \text{ for all } i, j$$

$$Cov[\alpha_i, X_{it}] \neq 0$$

Random effects, in contrast, are estimated by a ommon effects specification:

$$y_{it} = \alpha + \beta x + \varepsilon + \mu$$

$$E[u_i] = 0, Var[u_i] = \sigma_u^2, Cov[\varepsilon_{it}, u_i] = 0$$

$$Var[\varepsilon_{it} + u_i, \varepsilon_{is} + u_i] = \rho = \sigma_u^2 / \sigma^2$$

The two way random effects model takes the form

$$y_{it} = \alpha + \beta x + \varepsilon + \mu + w$$

We can rewrite this in the following form:

$$y_{it} = \alpha + \beta x + \sigma \varepsilon + \sigma \mu + \sigma w$$

All random effects have variance one. This model is identical to the previous one. The extension we consider here can be written

$$y_{it} = \alpha + \beta' x_{it} + \sigma_\varepsilon \varepsilon_{it} + \sigma_\mu \mu_i + \sigma_w w_t + \gamma \sigma_\mu \mu_i \sigma_w w_t$$

$$y_{it} = \alpha + \beta' x_{it} + \sigma_\varepsilon \varepsilon_{it} + \sigma_\mu \mu_i + \sigma_w w_t + \theta \mu_i w_t$$

That is, we add a product term which has a freely estimated additional 'effect' on the dependent variable.

The random parameters linear model is built around the structural equations.

$$y_i = \beta_i' x_i + \varepsilon_i, i = 1, \ldots, N \text{ groups},$$
$$\beta_i = \beta + \Delta Z_i + \Gamma v_i,$$
$$\text{Var}[\beta_i | z_i] = \Sigma = \Gamma \Gamma'$$

The Hildreth/Houck/Swamy variant of the random coefficient model is

$$y_i = \beta_i' x_i + \varepsilon_i, i = 1, \ldots, N \text{ groups},$$
$$E[\varepsilon_i | x_i] = 0, \text{Var}[\varepsilon_i | x_i] = \sigma_i^2 I,$$
$$\beta_i = \beta + v_i,$$

The coefficient vector within the group is a random draw from a distribution with overall mean β which we seek to estimate. The model assumes that parameters are randomly distributed with possibly heterogeneous (across individuals) mean.

$$E[\beta_i | z_i] = \beta + \Delta z_i 0, \text{Var}[\beta_i | z_i] = \Sigma$$
$$\beta_i = \beta + \Delta z_i + \Gamma v_i$$

The heterogeneity term is optional. It may be assumed that some of the parameters are nonrandom.

The nonlinear least squares estimator, general method of moments, presented in the preceding section on the least squares criterion

$$M(\beta) = \varepsilon(\beta)' \varepsilon(\beta)$$

minimizes the simple sum of squares of a set of residuals. The more general estimation criterion allows for instrumental variables.

$$M(\beta) = \varepsilon(\beta)' Z (Z' \Omega Z)^{-1} Z' \varepsilon(\beta)$$

The GMM criterion is

$$q = \overline{M}' \Sigma \overline{M}$$

where

$$\overline{m} = \frac{1}{n} \sum_{i=1}^{n} m_i(\beta, x_i)$$

Based on a set L of 'orthogonality conditions'

$$E[m_i(\beta, x_i)] = 0$$

This estimator of β is based on the GMM criterion.

The Tobit random effects model with censored data or truncation is based on the same latent regression. But the difference lies in the treatment of the common effect.

$$y^* = x_{it}' \beta + \varepsilon_{it} + \mu_i$$

$\varepsilon_{it}, \mu_i \sim$ bivariate normal with means $(0, 0)$, variances (σ^2, ω^2) and correlation 0.

Data are observed by the mechanisms

$y^* = \text{Max}(L_{it}, y_{it}^*)$ for the tobit model and

$y^* = y_{it}^*$ if $y_{it} \ge L_{it}$ and unobserved otherwise for the truncation model.

The essential assumptions are that the random effect is the same in every period and the unique effects, ε_{it} is uncorrelated across periods. All effects are uncorrelated across individuals. Under the Tobit model, let $d_{it}=1$ if $y_{it} > L_{it}$ (uncensored) and 0 otherwise. Then, the density of the observed random variable, y_{it} is

$$f(y_{it} | u_i, d_{it} = 0) = \text{Prob}[y_{it} \le L_{it}] = \Phi[(L_{it} - x_{it}'\beta - u_i)/\sigma] \quad \text{censored}$$

$$f(y_{it} | u_i, d_{it} = 1) = (1/\sigma)\phi[(y_{it} - x_{it}'\beta - u_i)/\sigma] \quad \text{uncensored}$$

Formulating the log likelihood function gives:

Conditioned on ui, the observations are independent. The joint density of the Ti observations for group i is the product of the individual densities;

The unconditional density is obtained by integrated ui out of the conditional density

The loglikelihood function is

$$\log L_{tobit} = \sum_{i=1}^{n} \log \left\{ \int_{-\infty}^{\infty} \frac{1}{\omega\sqrt{2\pi}} \exp\left(-\frac{u_i^2}{2\omega^2}\right) \prod_{t=1}^{T_i} \left[\Phi\left(\frac{L_{it} - x_{it}'\beta - u_i}{\sigma}\right) \right]^{1-d_{it}} \left[\frac{1}{\sigma} \phi\left(\frac{y_{it} - x_{it}'\beta - u_i}{\sigma}\right) \right]^{d_{it}} du_i \right\}$$

The function is to be maximized with respected to (β, σ, ω)

$$\log L_{truncation} = \sum_{i=1}^{n} \log \left\{ \int_{-\infty}^{\infty} \frac{1}{\omega\sqrt{2\pi}} \exp\left(-\frac{u_i^2}{2\omega^2}\right) \prod_{t=1}^{T_i} \left[\Phi\left(\frac{L_{it} - x_{it}'\beta - u_i}{\sigma}\right) \right]^{-1} \left[\frac{1}{\sigma} \phi\left(\frac{y_{it} - x_{it}'\beta - u_i}{\sigma}\right) \right] du_i \right.$$

3. Empirical Analysis

The IPAT model for a panel-data sample of the 76 provinces of Thailand during the period 2001-2008 has derived the empirical model by taking logarithms of equation (1). Total observations = 76*8 or 608.

The selections of various panel models are selected by restriction. In table1, the Chi squared statistic based on likelihood functions and F statistic based on the sums of squares are used for testing the restriction of fit in the regression; the null hypotheses of no time effects is rejected.

The Hausman test shows the consistency of model coefficients specified with random effect in the table 2. The rejection of the null hypothesis is likely to be due to the presence of random effects. The random and time effects in panel model corrected for heteroscadasticity are estimated. However, the negative sign of the emissions-population elasticity is lower than unity (-0.008) and the estimated coefficient is not significant with a negative sign. The effect of a 1% increase in GDP per capita is an increment in CO_2 of 1.11%. The contribution of the weight of final energy use per person (0.92%) is significant in the same direction.

The Hildreth, Houck,and Swamy random coefficients model is a linear regression in which the coefficient vector within the group is a random draw from a distribution with an overall mean. A chi squared test of this model against the alternative of the classical regression (no randomness of the coefficients) can be rejected. The randomness of the parameter is interpreted simply as latent heterogeneity. A model assuming that parameters are randomly distributed with possibly heterogeneous mean (across individuals) is fitted with panel data. Moreover, multilevel and multiple effects random parameter models are used so that the effects can be defined at any level of aggregation. The time, province and the interaction between time and province may be included in the model. In table 4, the parameter showing a negative sign for the emissions-population elasticity is lower than unity (-0.009) is not significant. The effect of a 1% increase in GDP per capita is an increment in CO_2 of 1.12%; and the contribution of the weight of the final energy use per person is 0.92%, significant in the same direction.

The random effects model with censored data is based on the same structure in every period and the unique effect that the residual is uncorrelated across periods. All parameters show a positive sign. The emissions-population elasticity is lower than unity (0.003) and the estimated coefficient is significant. The effect of a 1% increase in GDP per capita is an increment in CO_2 of 1.0%, the contribution of the weight of the final energy use per person (0.62%) is significant and in the same direction.

On the other hand the series may be non stationary. When the data are non-stationary, a matter of great disquiet is the danger of spurious regressions. The unit root tests reveal non stationarity for panel data (Levin *et al.*, 2002; and Im *et al.* 2003). The former test assumes a common AR structure for all series, whereas the latter allows for different AR coefficients in each series. Results are presented in Table 3. Both tests indicate that for almost all series in the model we must reject the null hypothesis of non-stationarity at I(1) . Only for the log of the proportion of population per province may one not reject the null hypothesis at I(1).

We estimated a dynamic panel data model in order to consider the possibility that actual emissions depend upon past emission levels and to give more flexibility to the estimation procedure. We applied the Generalized Method of Moments (GMM) method to the transformed series (first differences) and used as valid instruments all the exogenous variables and the second lag of the dependent variable. The results obtained by estimating the model in first differences (Table 2) show that population growth presents a non significant estimated coefficient. However, it changes the direction of sign. The preferred model is the dynamic specification estimated with the generalized method of moments technique, the series in first differences, instruments for all the exogenous variables in the model, and the second lag of the endogenous variable. The column of GMM results shows that the emissions-population elasticity is lower than unity (0.072) and the estimated coefficient is not significant. The effect of a 1% increase in GDP per capita is an increment in CO_2 of 0.76%; the contribution of the weight of the final energy use per person is 0.48%.

We provide several Pedroni panel cointegration test statistics which evaluate the null against both the homogeneous and the heterogeneous alternatives (Pedroni 1999, 2004; Kao 1999; Maddala and Wu, 1999; and a Fisher-type test using Johansen's test methodology). In this research, six of the eleven statistics reject the null hypothesis of no cointegration at the conventional size of 0.01.

4. Discussion

The results obtained for Thailand show a lower contribution of some of the explanatory variables (population and affluence) in explaining the variability of CO_2. The emissions-population elasticity is much lower, and significant for Thailand, when the model is estimated by the Tobit model.

A great number of studies confirm an overall upward trend in global emissions along the last decades that share two characteristics. First, emissions have grown faster than population and second, this relationship is more pronounced for developing countries than for developed countries (Shi, 2003; MacKellar *et al.,* 1995). However, such results might be due to the presence of heterogeneity in their sample since they include time, province, and the interaction term between time and province in multilevel and multiple effects random parameter models, but the coefficient has a negative sign and is not significant. CO_2 emissions also depend upon residential energy consumption, automobile transport and other factors attached to the urbanization processes, making uncertain the implications from the regression results for a declining population. An increase of 1% in GDP per head causes an approximate increase in CO_2 emissions of 1% (i.e., there is unitary elasticity of emissions). We found the effect of income to be greater than the effect of population growth. It is possible that the effect of income distribution and residential energy consumption in Thailand are very important to CO_2 emissions.

5. Conclusions

We have conducted a multivariate analysis of the determinants of carbon dioxide emissions aross 76 provinces in Thailand during the period 2001-2008. The usual assumption of unitary elasticity in the emission-population relationship has been relaxed.

In our model, population was introduced as a predictor, together with affluence per capita and the level of environmentally damaging technology, proxied by energy use per unit of consumption. Affluence was measured by GDP per capita in PPP.

We have applied several econometric estimation methods to the panel data. The results show different patterns for Thailand. The emission-population elasticity is lower than unity. The results obtained for Thailand show a lower contribution of some the explanatory variables (population and affluence) in explaining the variability of CO_2. The effect of income dominates that of population growth. Nevertheless, it remains unclear whether a demographic decline will restrain CO_2 emissions. According to our study, all these variables from the Tobit model significantly influence the volume of CO_2 emissions. Nevertheless, we must be cautious about the conclusions drawn, due to the lack of homogeneity in the statistical data for the entire sample of provinces. In this sense, further research with more data and alternative exogenous variables would contribute to improving the knowledge of the demographic, economic and environmental phenomena under study.

Table 1: Test statistics for the various classical panel models

MODEL	LOG-LIKELIHOOD	SUM OF SQUARES	R-SQUARED	RESTRICTION	CHI-SQUARED	D.F.	PROB.	F-statistic	NUM.	DENOM.	P VALUE
(1) CONSTANT TERM ONLY	-868.79	620.27	0.00	(2) VS (1)	1325.86	75.00	0.00	55.70	75.00	532.00	0.00
(2) GROUP EFFECTS ONLY	-205.86	70.07	0.89	(3) VS (1)	1317.99	3.00	0.00	1558.02	3.00	604.00	0.00
(3) X - VARIABLES ONLY	-209.80	70.98	0.89	(4) VS (1)	1539.13	78.00	0.00	78.48	78.00	529.00	0.00
(4) X AND GROUP EFFECTS	-99.23	49.34	0.92	(4) VS (2)	213.27	3.00	0.00	74.09	3.00	529.00	0.00
(5) X IND.&TIME EFFECTS	-83.71	46.88	0.92	(4) VS (3)	221.14	75.00	0.00	3.09	75.00	529.00	0.00
-	-	-	-	(5) VS (4)	31.03	7.00	0.00	3.90	7.00	522.00	0.00

Note: (1) no group effects or xs
(2) group dummies only
(3) regressors only
(4) xs and group effects
(5) time effect for each period

Table 2: the result from various classical panel models, Tobit model, GMM, Random parameter models

	OLS			FIX EFFECT			RANDOM EFFECT			RANDOM EFFECT (VARY IN TIME)			RANDOM EFFECT (VARY IN TIME & HETERO)		
	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB
CONSTANT	-2.115	0.169	***	-	-	-	-2.099	0.262	***	-2.122	0.259	***	-2.099	0.259	***
LP	-0.009	0.021	-	1.549	0.974	-	-0.008	0.033	-	-0.008	0.033	-	-0.008	0.033	-
LA	1.118	0.017	***	1.084	0.127	***	1.117	0.026	***	1.119	0.026	***	1.117	0.026	***
LT	0.918	0.034	***	0.941	0.657	***	0.923	0.043	***	0.959	0.043	***	0.923	0.043	***
Hausman-test										2.77(0.4) Chi-square (prob)					

Note: ***reject null hypothesis at 1%, ** reject null hypothesis at 5%,* reject null hypothesis at 10%
LP = the proportion of population
LA = in GDP per capita
LT = energy use per person

Table 3: the result from Tobit model, GMM, Random parameter models

	TOBIT(2CENSORED)			PANEL GMM EGLS						RANDOM PARAMETER MODEL					
	RANDOM EFFECTS			CROSS-SECTION RANDOM EFFECTS			PERIOD FIXED (DUMMY VARIABLES)			THE HILDRETH,HOCK, AND SWAMY' RADOM COEFFICIENTS MODEL			MULTILEVEL AND MULTIPLE EFFECTS RANDOM PARAMETER MODELS		
	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB	COEFFICIENT	STD	PROB
CONSTANT	-0.935	0.087	***	-0.120	0.524					-2.753	0.076	***	-2.115	0.189	***
LP	0.032	0.011	***	0.072	0.055		-0.693	0.535		-0.090	0.010	***	-0.009	0.024	
LA	1.001	0.008	***	0.762	0.354	**	0.704	0.129	***	1.162	0.008	***	1.118	0.019	***
LT	0.619	0.006	***	0.488	0.239	**	0.360	0.078	***	1.165	0.012	***	0.918	0.029	***
LI(-1)	-	-	-	0.455	0.046	***	0.371	0.024	***	-	-	-	-	-	-
LI(-2)	-	-	-	0.191	0.029	***	0.223	0.027	***	-	-	-	-	-	-
J-statistic				45.25(0.01) Chi-square (prob)						33.54(0.04) Chi-square (prob)					

Note: ***reject null hypothesis at 1%, ** reject null hypothesis at 5%,* reject null hypothesis at 10%
LI(-1) = CO_2 emission in 1 lag
LI(-2) = CO_2 emission in 2 lag
LP = the proportion of population
LA = in GDP per capita
LT = energy use per person

Table 4: the panel unit root test

	SERIES: LI		SERIES: D(LI)		SERIES: LP		SERIES: D(LP)		SERIES: LA		SERIES: D(LA)		SERIES: LT		SERIES: D(LT)	
METHOD	STATISTIC	PROB	STATISTIC	PROB	STATISTIC	PROB	STATISTIC	PROB	STATISTIC	PROB	STATISTIC	PROB	STATISTIC	PROB	STATISTIC	PROB
LEVIN, LIN & CHU T	-17.805	***	-42.725	***	-6.075	***	2.387	-	-5.723	***	-31.357	***	-5.864	***	-17.629	***
IM, PESARAN AND SHIN W-STAT	-2.601	***	-13.701	***	4.558	-	3.195	-	3.177	-	-5.107	***	0.768	-	-4.201	***
ADF – FISHER CHI-SQUARE	230.878	***	341.264	***	109.174	-	99.238	-	122.976	-	269.090	***	142.097	-	241.620	***
PP – FISHER CHI-SQUARE	221.651	***	534.390	***	436.684	***	427.682	***	273.634	***	416.543	***	261.005	***	487.425	***

Note: ***reject null hypothesis at 1%, ** reject null hypothesis at 5%,* reject null hypothesis at 10%

Table 5: the panel co-integration test

PEDRONI RESIDUAL COINTEGRATION TEST				
NULL HYPOTHESIS: NO COINTEGRATION			WEIGHTED	
	STATISTIC	PROB.	STATISTIC	PROB.
PANEL V-STATISTIC	-3.97029	-	-4.79227	-
PANEL RHO-STATISTIC	3.574206	-	4.033625	-
PANEL PP-STATISTIC	-19.9206	***	-17.7035	***
PANEL ADF-STATISTIC	-10.5027	***	-9.14357	***
ALTERNATIVE HYPOTHESIS: INDIVIDUAL AR COEFS. (BETWEEN-DIMENSION)				
GROUP RHO-STATISTIC	8.047688	-	-	-
GROUP PP-STATISTIC	-22.4952	***	-	-
GROUP ADF-STATISTIC	-9.79954	***	-	-

Note: ***reject null hypothesis at 1%, ** reject null hypothesis at 5%,* reject null hypothesis at 10%

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