Journal of Energy and Power Engineering 7 (2013) 1448-1456

Analyzing the Share Composition of CO_2 Emissions in Asian Countries

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Received: November 10, 2012 / Accepted: February 01, 2013 / Published: August 31, 2013.

Abstract: This paper is concerned with the fossil fuel composition of carbon emissions in 10 selected Asian countries. It assesses how economic development may affect this composition through various channels. This paper contributes to the debate on the EKC (environmental Kuznets curve) puzzle, which hypothesizes an inverted U-shaped relationship between per capita income and pollution. The paper examines the EKC hypothesis in an empirical analysis of channels that may allow for this effect. In particular, a specific subset of this general paradigm is investigated using a fractional multinomial logit model to assess how indicators associated with economic development and energy prices affect carbon emissions from coal relative to those of natural gas and oil.

Key words: Asia, energy, carbon dioxide emissions, CO_2, natural gas, coal, oil.

1. Introduction

"Empirical verification of the Kuznets environmental curve should be seen as evidence for the notion that, eventually, income growth will, one way or another, tend to 'fix' environmental problems" [1].

"…economic liberalization and other policies that promote GNP (gross national product) growth are not substitutes for environmental policy" [2].

The above quotations summarize the discussion that motivates this paper. Advocates of the EKC (environmental Kuznets curve) claim that the relationship between pollution and per capita income is characterized by an inverted U-shaped curve (possibly parabolic), suggesting that countries pollute less as they grow. A vast amount of empirical literature has been directed to verifying this relationship, but the findings from the majority of these studies have been questioned (for review and critique) [3-6]. The critiques address issues with methodology (functional form), the use of multi-country panel data, and the quality of the data (one problem being the use of different measures of "pollution"). This literature has spurred EKC skeptics who argue that such evidence is weak [3, 5, 7], and that output growth is not a substitute for environmental policies [2]. Moreover, Refs. [8-10] find evidence of a monotonous relationship between per capita income and pollution in their multi-country studies.

This paper argues that simply fitting an inverted "U"-curve to multi-country panel data per se is not necessarily relevant. For instance, the low-income countries to the left of this curve may have a completely different economic structure and policies compared to the countries to the right of that curve, meaning that comparisons carried out this way are not very meaningful. What really matters are the channels that may allow a country to pollute less heavily as output grows. Ref. [11], in the seminal contribution that popularized the EKC, subscribe to this view. They contemplated three main channels: The first channel was an increase in the scale of production; the

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second, a change in the composition of production; and the third was shifts in production techniques. A more recent multi-country study in Ref. [12] advocates "decomposing" the EKC by considering different variables linked to specific channels.

On the surface, a relationship between income per capita and pollution may or may not be consistent with EKC, but this is not the main point that this paper addresses when analyzing data for Asian countries. Instead, the general question to be addressed is "What changes are necessary in the structures of Asian economies to reduce pollution?" For example, in China and India, CO_2 emissions from coal use account for about 80% and 65% of total CO_2 emissions, respectively. It is interesting to see what changes in their economic structures are necessary to reduce coal intensity. The number of channels involved in this process makes the research prohibitively broad; hence the paper addresses a subset of this problem. For pollution data, statistics on CO_2 emissions produced from using fossil fuels—coal, oil and natural gas are used.

For the methodology, individual fractional shares of CO_2 emissions coming from the use of coal, natural gas and oil are considered in a fractional multinomial logit model. The channels that explain changes in the fossil fuel composition of emissions are analyzed through explanatory variables linked to economic development and other economic factors such as energy prices. As an economy develops, it is expected that coal would be replaced with oil and/or natural gas. This change is associated not only with growing national wealth funding technological advances in energy infrastructure, but also with the changing urban population, the transition from export-driven to consumption-driven growth, and energy prices. The economic structures of the Asian countries under study share many common features while being at different stages of development. A number of the selected Asian countries tend to be dependent on export-led growth, have a large rural population, use a significant amount of coal, and lack energy infrastructure. In their growth process, these features tend to revert. It is likely that this homogeneity in the development pattern will allow for the extraction of insightful information from a pool data set, taking into account country idiosyncratic features. This analysis does not include renewable energy as an alternative to fossil fuels. The estimation results will allow for the identification of changes in the economic structures of Asian economies to achieve certain coal emission targets. With this information, some assessment can be made of the extent to which economic development can replace specific environmental policies in reducing CO_2 emissions in selected Asian countries. This paper contributes to the future of the post-Kyoto environmental policy debate, and towards solving the paradigms associated with the EKC puzzle.

The balance of this paper is as follows. Section 2 discusses the data used in the empirical model and the intuition behind the modeling decisions. Section 3 outlines the fractional multinomial logit model. Results are analyzed in Section 4. Section 5 concludes the paper with a discussion on policy implication of the results.

2. Material and Methods

To investigate the determinants of the relative shares of CO_2 emissions from fossil fuels, a panel dataset is constructed, combining annual data for 10 selected economies in Asia—China, India, Indonesia, Japan, South Korea, Malaysia, Philippines, Singapore, Thailand and Vietnam from 1984 to 2009.

The paper concentrates attention on the following measures of relative CO_2 emissions from fossil fuels:

$$C_1 = \frac{\mathrm{CO_2\ Emissions\ from\ Coal}}{\mathrm{Total\ CO_2\ Emissions\ from\ Coal, Gas\ and\ Oil}}$$
$$C_2 = \frac{\mathrm{CO_2\ Emissions\ from\ Gas}}{\mathrm{Total\ CO_2\ Emissions\ from\ Coal, Gas\ and\ Oil}}$$
$$C_3 = \frac{\mathrm{CO_2\ Emissions\ from\ Oil}}{\mathrm{Total\ CO_2\ Emissions\ from\ Coal, Gas\ and\ Oil}} \tag{1}$$

The data used for the calculation of these emission shares are provided by the EIA (Energy Information Administration, 2011) and measured in million metric tons of CO_2 emissions. The variables C_1, C_2 and C_3 measure the relative contribution of CO_2 emissions from the use of each fossil fuel to total carbon dioxide emissions. With the use of a fractional multinomial logit model, the question that is to be addressed is how different variables or channels affect the social choice of the composition of fossil fuel emissions. As for the exogenous variables explaining the choices, four different channels are considered. First, the urbanization ratio (U) of the economies in the sample is considered. High CO_2 emissions from coal use (C_1) in China and other countries are often linked to rural areas that do not have access to modern energy infrastructure that would allow for the use of an energy source other than coal, such as natural gas. This is a situation which will almost certainly change as Asian economies develop. It is expected that increased urbanization to lead to a decline in the share of coal emissions and a rise in the oil emissions share (C_3) due to better infrastructure and increased use of transportation. Second, consider an EX (exports index). This variable changes significantly at different stages of development. Most Asian economies are typically export-led and focused on producing labor-intensive manufactured goods. The production of these goods requires large amount of energy and, with limited infrastructure, the use of highly-polluting energy sources such as coal becomes necessary. As Asian economies develop, they tend to rely less on labor-intensive manufactured exports and more on services exports and supplying the domestic market (e.g., Singapore, South Korea, Japan and possibly China and India in the near future). Third, consideration is given to the level of GDP_{PC} (GDP per capita) as a measure of the country's capacity to improve infrastructure that would generate cleaner energy. In this context, GDP per capita enters as a linear explanatory variable and the characteristic curvature of the EKC could emerge when all the factors taken together allow for it.

A fourth factor affecting the choices of the model relates to energy prices (PO). Oil prices have been subject to dramatic changes over time while natural gas prices are more difficult to measure, as a global natural gas price does not exist. Natural gas prices are typically negotiated between two transacting countries and set in bilateral agreements. However, an examination of LNG (liquefied natural gas) prices for Japan, China and South Korea suggests a very high correlation with international oil prices. Simplifying the model to avoid autocorrelation, the WTI price is used as an indicator of both the oil and natural gas price. In the equations for oil and natural gas, this variable is interpreted as the price of the resource. In the coal equation, it is interpreted as the price of substitutes. The coal price presents some difficulties as the markets are much more segmented and often highly regulated. Moreover, it is worth noting that coal is only an imperfect substitute for natural gas and oil in the sense that production plants designed for oil and/or natural gas can not switch to coal. Thus, coal demand is generally inelastic to coal price in the short run whereas it may react to the price of substitutes and the changes in economic structure over the longer run. Altogether, incorporating a proxy for oil/natural gas price, the economic development indicators, and country-specific constants are enough to capture the social choices of interest. Table 1 provides a more precise definition of the explanatory variables in the model.

3. Theory and Calculation: The Fractional Multinomial Logit Model

To model changes in fossil fuel share of CO_2 emissions, a fractional multinomial logit specification is implemented, utilizing the estimation techniques in Refs. [16-21]. In this setup, the allocation of carbon dioxide emissions from the use of coal, natural gas and oil are modeled as a social choice. In other words, the observed fractional choices are seen as an outcome

Table 1 Description of explanatory variables.

Variables	Description, [Reference]
GDPPC	Gross domestic product per capita, at constant prices, in 2005 US$ [13]
EX	Exports index, 2,000 = 100, [14]
U	Urban population as % of total population, [13]
PO	WTI crude oil price, in 1984 US$ (Source: AEI Statistics, [15]
Y_i	Vector for observation *i* in the panel containing all of the above variables

emerging from a balance of forces between the interests of governments, industries, and participants in energy markets, environmental policies, and consumers. In line with this interpretation, it is proposed that the model of emission choices follows this objective welfare function:

$$\mathrm{Max}_{C_{j=\{1,2,3\}}} U = U_1(C_1) + U_2(C_2) + U_3(C_3)$$
$$U_1(C_1) = \gamma_1 + \gamma_{c1} + \beta_1{}'Y_i + \varepsilon_{i1}$$
$$U_2(C_2) = \gamma_2 + \gamma_{c2} + \beta_2{}'Y_i + \varepsilon_{i2}$$
$$U_3(C_3) = \gamma_3 + \gamma_{c3} + \beta_3{}'Y_i + \varepsilon_{i3}$$

Subject to:

$$C_1 + C_2 + C_3 = 1, C_{j=1,2,3} \in (0,1) \qquad (2)$$

where, Y_i is the vector of relevant explanatory variables from Table 1. The coefficients to be estimated are given by β_j, γ_j and the country-specific factors γ_{cj}. The index $i = (1, \ldots, n)$ is used to denote the observations in the panel dataset. Following the tradition of the fractional multinomial logit model, the disturbances ε_i are assumed to be independently and identically distributed according to a Gumbel (also known as type-I) extreme-value distribution.

An important assumption in this model is that the observed (proportional) choices $C^{obs}_{j,j\epsilon\{1,2,3\}}$ arise from a welfare maximization environment. To see how this idea is implemented, consider the following comparison with an extreme hypothetical situation. If the world economy consisted of one single "Robinson Crusoe" individual, his optimal choice would be:

$$U_j(C_j^{opt}) > U_q(C_q) \quad \forall\, q \in \{1,2,3\}, q \neq j$$

and the decision would be to consume $C_j^{opt} = 1$, i.e. 100% of the *j* fossil fuel and 0% of the other types of fuel. The model incorporates realistic assumptions. First, the optimal choices observed in the data aggregates are of fractional, rather than binary, in nature. Second, it is assumed that these fractional choices emerge as a balance of different economic forces embodied in $\beta_j{}'Y_i$ system. Third, the modeling allows for a stochastic component affecting the decision-making process. Incorporating all these assumptions allows for the modeling of *j* fractional choices as:

$$C_j^{obs} = \Pr\left(C_j^{obs} = C_j^{opt} \middle| C_q^{obs}, Y_i, \gamma_j, \gamma_{cj}, \beta_j\right) \forall\, j \in \{1,2,3\},\ q \in \{1,2,3\}\ q \neq j$$

Then, the next step consists in defining the above probability function and the algorithm to estimate the parameters of the model. For that purpose, the following short-hand notation is used:

$$\widehat{U}_j(C_j) = \gamma_j + \gamma_{cj} + \beta_j{}'Y_i = \theta'_j X_i$$

where, $X_i = [1_i, d_{countries}, Y_i]$, $d_{countries}$ is a country indicator dummy variable, and $\theta_j = (\gamma_j, \gamma_{cj}, \beta_j)$. Then, the probability of choice *j* is defined as:

$$\Pr\left(C_j^{obs} = C_j^{opt} \middle| \theta, X_i\right) = \Pr\left\{U_j\left(C_j^{opt}\right) > \mathrm{Max}_{q=1,2,3,q\neq j}\left[U_j\left(C_q\right)\right]\right\}$$
$$= \Pr\left[(\theta_j{}'X_i + \varepsilon_{ij}) > \mathrm{Max}_{q=1,2,3,q\neq j}(\theta_q{}'X_i + \varepsilon_{iq})\right] \qquad (3)$$

Noting that the Gumbel extreme-value distribution has the c.d.f. $F(\varepsilon_{ij}) = \exp\left[-\exp(-\varepsilon_{ij})\right]$, the above can be written as:

$$\Pr\left(C_j^{obs} = C_j^{opt} \middle| \theta, X_i\right) = P_j = f_j(\theta_j{}'X_i) = \frac{\exp(\theta_j{}'X_i)}{\sum_{m=0}^{J} \exp(\theta_m{}'X_i)} \qquad (4)$$

Eq. (4) represents a standard fractional multinomial logit model as used in previously cited works.

4. Theory and Estimation: The Fractional Multinomial Logit Model

4.1 Estimating the Multinomial Logit Model

The parameters θ in the above model can be estimated by maximizing the following log-likelihood objective function:

$$LogL = \sum_{i=1}^{n} \sum_{j=1}^{3} C_{ij} Log\, P_j = \sum_{i=1}^{n} \sum_{j=1}^{3} C_{ij} Log \left[\frac{\exp(\theta_j{}' X_i)}{\sum_{m=0}^{J} \exp(\theta_m{}' X_i)} \right] \quad (5)$$

The first and second derivatives of this log-likelihood function are given by:

$$\frac{\partial LogL}{\partial \theta_j} = \sum_{i=1}^{n} (C_{ij} - P_j) X_i \,, \frac{\partial^2 LogL}{\partial \theta_l \partial \theta_m} = \sum_{i=1}^{n} [-(1_{(l=m)} P_{il} P_{im}) X_i X_i{}'] \quad (6)$$

Before doing the estimation, it is worth explaining how the covariance matrix is specified. In the multinomial logit literature, it has become a common practice to use "robust" covariance matrices which are consistent with latent heteroskedasticity, a frequent problem in panel data estimations (for instance, different countries may have different disturbances). To see how the robust covariance matrix is computed, define the cluster-*C* gradient and Hessian matrices as $g_{ic} = \{\partial LogLik_{ic} / \partial \theta_j\}$ and $H_{ic} = \{\partial^2 LogLik_{ic} / \partial \theta_j \partial \bar{\theta}\}$, respectively. In the "uncorrected" version, the asymptotic covariance matrix is given by:

$$V_H = -H^{-1} = \left(-\sum_{c=1}^{C} \sum_{i=1}^{n_C} H_{ic} \right)^{-1}$$

and the "robust" estimator of the covariance matrix used in this paper is given by:

$$\text{Asy. Var}[\hat{\theta}_j] = V_H \frac{C}{C-1} [\textstyle\sum_{c=1}^{C} (\sum_{i=1}^{n_c} g_{ic})(\sum_{i=1}^{n_c} g_{ic})'] V_H \quad (7)$$

As this covariance matrix is asymptotic, the log-likelihood function is globally concave [17]. To estimate the parameters, the program *NLogit*^{TM} 4.0 [18] is used, where this maximizes the above log-likelihood function using Newton's method. To get a closed log-likelihood function where the parameters can be identified, the estimation algorithm requires normalizing the coefficients of one of the welfare functions in Eq. (2) to zero. The coefficients in $U_1(C_1)$ are normalized to zero.

The estimation results are summarized in Table 2. Overall, introducing the selected explanatory variables produce a great improvement compared with the constants-only model. The *t*-values associated with the explanatory variables and the country-specific coefficients suggest that they are highly significant in most cases. It is worth noting that Table 2 are estimates of the weights in the welfare functions and do not provide any information about how the explanatory variables affect the choices. A sensitivity analysis is presented in the next section.

4.2 Computing Marginal Effects and Elasticities

This section is concerned about processing the information from the estimation to analyze how changes in the relative CO_2 emissions from coal, natural gas and oil are affected by the explanatory variables. To carry sensitivity analysis and see how each of the explanatory variables and the factors affect the fitted choices $\hat{P}_{j=1,2,3} = f_j(\hat{\theta}' X) = E(C_j)$, thematrix of marginal effects (derivatives) is computed in the following way [18]:

$$\hat{\delta}_{j.X} = \frac{\partial \hat{P}_j}{\partial X} = f_j(\theta' X)(\hat{\theta}_j - \bar{\theta}) \quad (8)$$

where:

$$\bar{\theta} = \sum_{j=1}^{3} f_j(\theta' X) \hat{\theta}_j$$

It becomes clear that neither the sign nor the magnitude of $\delta_{j.X}$ need bear any similarity to those of $\hat{\theta}_j$ (Table 2). The following covariance matrix of $\delta_{j.X}$ to compute *t*-statistics can then be obtained:

$$\text{Asy.} \widehat{\text{Var}}[\delta_{j.X}] = G_j \text{Asy. Var}[\hat{\theta}_j] G_j' \quad (9)$$

where:

$G_j = \partial \delta / \partial \beta' = f(\hat{\theta}' X)\mathrm{I} + [df'(\hat{\theta}' X) / d(\hat{\theta}' X)] \hat{\theta}' X.$

It is also possible to calculate the elasticities associated with the above marginal effects with:

$$\hat{E}_{j.X} = \hat{\delta}_{j.X} \frac{X}{f_j(\hat{\theta}' X)} \quad (10)$$

The analysis of the effects of explanatory variables on the emissions shares is important. It is worth noting that both the marginal effects and the elasticities depend on the values of X. Table 3 shows the marginal effects for mean values $X = \bar{X}$, their *t*-values and the elasticities associated with them. In addition, it also reports the average of the elasticities calculated for each observation $X_{i=1,\dots,n}$ in the sample.

5. Discussion

Table 3 reports marginal effects and elasticities for the vector of explanatory variables in each fuel type

Table 2 Estimation results.

Statistic summary		Equation $U_2(C_2)$ (t-values)	Equation $U_3(C_3)$ (t-values)
P_{OIL}: Mean = 19.68, Std. Dev. = 9.39; GDP_{PC}: Mean = 7,309.86, Std. Dev. = 11,219.66; EX: Mean = 101.69, Std. Dev. = 86.43; U: Mean = 27.049, Std. Dev. = 28.22.	Parameter estimates		
	Coefficients $\hat{\beta}_j$:		
	PO	-0.01768 (-3.652)	-0.01664 (-4.721)
Estimation properties	GDP_{PC}	0.725E-4 (3.538)	-0.320E-4 (-2.553)
	EX	0.00239 (3.152)	-0.00048 (-0.924)
Number of observations = 260;	U	0.06723 (2.174)	0.08416 (5.103)
Number of parameters = 28; LogLik (Model) = -194.4760;	Constant $\hat{\gamma}_j$:	-4.95783 (-13.146)	-2.21514 (-12.208)
LogLik (Constants Only) = -245.9275; LogLik (No Model) = -285.6392; Akaike information criterion = 1.71135; McFadden pseudo-R^2 = 0.2092;	Country-specific factors $\hat{\gamma}_{cj}$:		
LR statistic (Model vs. Constants Only) = 102.9046;	China	-	-
	India	1.52763 (12.239)	0.81220 (14.442)
Degrees of freedom for LR test = 26;	Indonesia	4.78035 (23.790)	2.95219 (26.771)
Pr [Chi-Sq. Statistic > Crit. Value] = 0.0000;	Japan	-1.4120 (-1.022)	0.52863 (0.758)
	Korea	-0.685623 (-0.568)	-0.89624 (-1.420)
Mean actual proportions	Malaysia	5.76206 (27.068)	3.93088 (30.857)
$C_1 = 0.3276$, $C_2 = 0.1187$, $C_3 = 0.5537$;	Philippines	1.98948 (6.842)	2.74870 (26.511)
	Singapore	1.20091 (0.439)	2.58552 (1.766)
Mean predicted proportions	Thailand	4.31742 (29.982)	3.07664 (49.979)
$\hat{P}_1 = 0.3276$, $\hat{P}_2 = 0.1187$, $\hat{P}_3 = 0.5537$.	Vietnam	2.25671 (11.714)	1.71504 (18.844)

Table 3 Marginal effects and elasticities.

	C_1 (Coal)				C_2 (Natural gas)				C_3 (Oil)			
	Mg. effect	t-value	Elasticity $X=\bar{X}$	Average elasticity	Mg. effect	t-value	Elasticity $X=\bar{X}$	Average elasticity	Mg. effect	t-value	Elasticity $X=\bar{X}$	Average elasticity
Variables GDP_{PC}	0.311E-5	1.436	0.10886	0.0977	0.869E-5	7.832	0.63904	0.6278	-0.12E-4	-7.256	-0.12476	-0.1359
EX	0.195E-4	0.222	0.00951	0.0060	0.00025	5.724	0.25295	0.2374	-0.00027	-3.556	-0.03924	-0.0522
U	-0.01356	-4.819	-1.75510	-1.7248	0.00023	0.105	0.06345	0.0938	0.01327	4.910	0.52120	0.5561
PO	0.00277	4.581	0.26099	0.2191	0.00044	-1.463	-0.08694	-0.1288	-0.00233	-4.154	-0.06636	-0.1095
Constant $\hat{\gamma}_j$	0.42316	13.556	-	-	-0.29160	-9.846	-	-	-0.13155	-3.884	-	-
Country factors												
India	-0.14912	-15.150	-0.07136	-0.0301	0.08093	8.290	0.08140	0.1227	0.06819	6.243	0.00986	0.0511
Indonesia	-0.52599	-26.772	-0.25170	-0.2904	0.22503	16.049	0.22633	0.1876	0.30096	17.486	0.04352	0.0048
Japan	-0.04646	-0.374	-0.02231	-0.0134	-0.16539	-1.740	0.16635	-0.1575	0.21185	2.137	0.03063	0.0394
Korea	0.14377	1.312	0.06881	0.0538	0.00024	0.003	0.00024	-0.0148	-0.14401	-1.453	-0.02082	-0.0359
Malaysia	-0.68784	-30.904	-0.32915	-0.4257	0.24264	15.920	0.24706	0.1505	0.44220	19.937	0.06394	-0.0326
Philippines	-0.43860	-23.122	-0.20988	-0.2127	-0.01087	-0.390	-0.01093	-0.0182	0.44947	13.897	0.06499	0.0577
Singapore	-0.39863	-1.580	-0.19075	-0.2528	-0.07026	-0.363	-0.07066	-0.1327	0.46889	1.955	0.06779	0.0057
Thailand	-0.53436	-35.612	-0.25571	-0.2764	0.17502	14.601	0.17603	0.1554	0.35934	21.343	0.05196	0.0313
Vietnam	-0.29476	-18.192	-0.14105	-0.0922	0.08413	6.117	0.08462	0.1335	0.21062	14.999	0.03045	0.0793

choice, with the preferred measure being the average elasticity. This conveys information from data variation in the whole sample to show the average percentage marginal impacts over the choice variables for a unit percentage change in the explanatory variables. The impact of each factor can be analyzed in turn.

5.1 U (Urbanization)

Urbanization has mixed impact on emissions shares. In this instance and as expected, U elasticity is found to have a negative and statistically significant impact on coal's share of emissions (-1.7248, *t*-statistic = -2.819), while having an insignificant impact on natural gas's share (*t*-statistic = 0.105) and a positive significant impact on oil's share of emissions (0.5561, *t*-statistic = 4.910). The negative relationship between urbanization and the use of coal indicates that as a country urbanizes, the less reliant they are on coal for production, power generation and heating uses. In addition, urbanization leads to an increase in the use of oil-fuelled transportation. Resulting from these two effects, the net effect on natural gas emission share proves to be insignificant.

5.2 GDP_{PC} (Per Capita GDP)

In looking at the impact of GDP_{PC} on coal, it is found that no statistically significant relationship can be established between GDP_{PC} and coal's share of total emissions (*t*-statistic = 1.436). By contrast, the elasticity with respect to natural gas is statistically significant and equal to 0.6278. As natural gas emissions account for 11.87% of the sample average (across country and time), this implies a particularly strong relationship between per capita income and a preference for natural gas use. A 10% increase in GDP_{PC} results in a 6.269% increase in natural gas's share of emissions. This raises the question as to why this effect is positive for natural gas and not for coal. One explanation is that the rise in the use of natural gas over this period was predominantly confined to several countries raising natural gas generating capacity from a low base—Japan, Malaysia, Indonesia and Thailand—whereas coal emission shares remain relatively unchanged in countries such as China and India. The impact of GDP_{PC} on oil's share of emissions suggests a negative statistically significant effect, although for every 1% increase in GDP_{PC}, there is only a 0.1359% decline in oil's share of emissions, a much more muted response in comparison to the estimate for natural gas. One explanation for this is the extent to which the oil shock in the early 1980s spawned improvements in car engine efficiency and move towards smaller cars. The relatively small size of the oil marginal effect estimate is indicative of the low level of substitution in transport fuels compared. In some instances, notably the Philippines, it is also a function of the historic decline of the use of oil in stationary generation. Overall, the estimates suggest that as countries become wealthier, they tend to substitute away from coal and to a lesser extent, oil and towards natural gas.

5.3 EX (Exports)

The impact of exports on the emission shares of the three fossil fuels tends to mirror those of per capita GDP. Exports elasticity is not a statistically significant explanatory variable of movements in coal emissions (*t*-statistic = 0.193). However, exports are significant in explaining movements in natural gas (0.2374 elasticity, *t*-statistic = 5.149) and oil (-0.0522 elasticity, *t*-statistic = -3.037) emission shares. It is possible that export growth in the sample has overall tracked growth in per capita GDP, i.e., a 1% increase in GDP_{PC} increases natural gas share of emissions by 0.6269%, while a 1% increase in exports increases natural gas's share of emissions by only 0.2374%. A few observations can be made to support this result. First, low export growth rates in the sample tend to be associated with high output growth. As both exports and output increase, the effects of output growth outweigh those of export growth. Second, countries with high export growth have seen only tentative shifts towards substitution into natural gas. This is particularly true for China.

5.4 Energy Prices (PO)

The impact of oil price on oil's share of emissions is statistically significant with an average negative elasticity of -0.1095 which reflects an inelastic demand. Furthermore, it is found that the impact of the oil price on the coal share is significantly positive (0.2191, *t*-statistic = 4.581). When comparing these figures, it has to be considered that emissions from coal are about 33% higher than that from oil on a per kilowatt basis in power generation [22]. WTI oil price (also used as a proxy to natural gas price) has a similar negative impact on relative natural gas emissions.

5.5 Country Specific Impacts

The signs of the country specific marginal effects in Table 3 provide information about idiosyncratic country's preferences or inherited endowments of fossil fuels. These marginal effects indicate how relative emissions will differ in each country with all the explanatory variables being equal to the panel sample mean. No dummy variable for China was used (these effects are incorporated into the intercept $\hat{\gamma}_j$). In relation to China, the country-correction dummies $\hat{\gamma}_j$ have no direct meaningful economic interpretation as they are capturing a broad array of effects, but the signs of the dummy coefficients are relevant for the analysis. Relative to China, virtually all other countries (except Korea) tend toward a lower share of coal emissions ceteris paribus. The findings on natural gas are at first glance more ambiguous, with Japan, Korea, the Philippines and Singapore all having country-specific intercepts not statistically different from China's. This is intuitively correct, as Japan and Korea are similar to China in terms of developing natural gas generation through slow-paced long-term LNG developments, while Singapore has no real presence in terms of coal emissions and the Philippines has had a substitution strategy via domestic production. The other five countries (India, Indonesia, Malaysia, Thailand and Vietnam) are less likely to have higher natural gas emissions relative to China. Again, this is a somewhat intuitive result, with this group still relying on coal to a large extent, the exceptions being Malaysia and Vietnam. Malaysia has a substantial domestic reservoir of natural gas which has been developed from the early 1980s. Vietnam saw a similarly dramatic decline in coal share of total emissions which is explained by the development of major hydroelectric projects in the 1980s [23]. Turning to oil emissions, average elasticities indicate that three countries have the country-specific intercepts which are not statistically different from those of China, these are: Japan, Korea, and Singapore. Malaysia is the only country with an intercept lower than China's, ceteris paribus. This is largely an artifact of the sample as Malaysia's early adoption of natural gas in the 1980s was not fully captured before the first observation of the sample in 1984. India, Indonesia, Philippines, Thailand and Vietnam have statistically significant and positive oil country factors, reflecting these countries' stable or growing reliance on coal in stationary generation. Vietnam is anomalous for reasons discussed above, with the shift towards hydro-electric power lowering stationary emissions.

These estimations allow for conclusions to be drawn as to how economic development factors and emissions interact. For instance, suppose a country has coal share emissions equal to the sample mean. Now, what changes in terms of urbanization and exports are needed in order to achieve a certain coal emission target over a 10 year period? Assuming a 6% per year growth rate in real per capita GDP (producing an impact of 7.7183% increase in coal emission share over 10 years) and constant oil prices, the average elasticities suggest the following: the maximum possible decline in exports (-100%) leads to a 0.27% decline in coal emission share, resulting in a net increase in coal emission share of 7.4483% after the increase in income is taken into account. An increase of 10% in the urbanization sample mean U = 27.0488 leads to a 17.248% decline in coal emission share which becomes 9.530% net of income effect.

From this analysis it seems clear that the existence of an EKC-type inverted "U" curve between coal share emissions and per capita GDP depends to a large extent on changes in urban population while changes in exports have little power to influence the shape of that curve.

6. Conclusions

This paper analyzes the various channels that influence the share composition of fossil fuel emissions using a fractional multinomial logit model. The main contribution of the model is the extraction of insightful information which draws from the experience of Asian economies that have similar economic characteristics but at different stages of development. The model allows for direct computation of elasticities that indicate the interaction between fossil fuel emission shares and selected economic development variables.

This empirical work allows for the re-examination of the question posed at the beginning of this paper: Is economic development a substitute for environmental policy? Based on the model, urbanization is the main determinant. If urbanization increased in a substantial way as Asian economies developed, it would reduce the share of coal CO_2 emissions and hence, overall emissions. If development policies get implemented that are oriented to increasing urban population, it would be expected that a substantial reduction in the intensity of coal in CO_2 emissions would follow. A different type of question is whether or not the aggregate levels of CO_2 emissions are reduced in major Asian economies as they continue to grow and as new environmental targets and emission reduction technologies get implemented. The balance of these effects is a question for future research.

Acknowledgments

The authors would like to acknowledge financial from the Australia-China Council.

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