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DOES THE DE-INDUSTRIALIZATION AND TERTIARIZATION PROCESS DECARBONIZE EMISSIONS IN ASIAN COUNTRIES?

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Abstract: *To date, slowdown trends in the global CO_2 emissions registered in 2012 to 2015 argue due to the transformation from an industrial based on a less-energy intensive services oriented. Nevertheless, inconsistent and insufficient evidence of the role of sectoral composition in influencing the carbon emissions is a serious academic and policy gaps that were overlooked. Thus, due the fact that Asian countries experiences a dramatic shift in phases of economic structure, this study aim to investigate whether the de-industrialization and tertiarization process might be the solution to the carbon emissions in Asian countries.* *As the structural heterogeneity exists widely across countries in Asian countries, this paper employs Stochastic Impact by Regression on Population, Affluence, Technology (STRIPAT) model as its analytical framework and estimate using the Dynamic Common Correlated Effects (DCCE) estimator to address the heterogeneity, cross-section dependence, and dynamic nature of carbon emissions. In sum, this study found that the de-industrialization moderating the CO_2 emissions in Asian countries, while the expansion of service sector bound to reduce the CO_2 emissions as presented in quadratic functional. Nevertheless, an N-shape relationship observe in cubic functional, thus there is no guarantee that long-term levels of pollution emissions will continue to fall as countries shifting to services-based economy. The finding of this study is important not only in term a value-added of current knowledge, but also in assisting the development of strategic planning and better sustainable policy to combat the growth of CO_2 emissions.*

Keywords: *Asian Countries; Sectoral Composition; CO_2 Emissions; STRIPAT; Dynamic Common Correlated Effects (DCCE)*

Introduction

Historically, the economic development not only accompanied with the switching from the agricultural sector to the manufacturing sector or known as the industrialization process, but also the transformation from industrial into services economy or known as tertiarization process (Kijima *et al*., 2010). Since the 19th century, the rapid growth of industrial sector in line with the expansion of energy-intensive activities that lead to greater carbon emissions (Poku, 2016). Interestingly, according to Marsiglio *et al*. (2016) the shrinking shares of manufacturing and simultaneously increase the share of the service sector will reduce the carbon emissions. Nevertheless, empirically studies that confirmed the tertiarization effect in lowering the carbon emissions considers scarce.

In this field Asian countries are a primary candidate and Asian country's merits investigation for three reasons. First, Asian countries experience a more rapid shift in economic structure compared to other regions and currently Asia takes the blamed as the main culprit for global carbon emission (Olivier *et al*., 2016). Second, the structural heterogeneity that exist in Asian countries as well as the cross-sectional dependence among Asian countries has been less considered by previous studies (Felipe *et al*., 2016). Second, by the year 2020, Asian countries aim to reduce the pollution emissions of the overall economy by 36-39 per cents, thus, a propose strategies to curb the pollution it is a serious academic and policy requirement.

The current study mainly provides three contributions, first, we adopt an alternative indicator as a proxy of affluence effect in the non-linear STRIPAT framework, namely, industrial and services value added. Moreover, the Kuznets theory of inverted U-shaped examine by the inclusion of quadratic and cubic term of both sectors to explain the carbon emissions (herewith denoted as CO_2 emissions) which not existence in Asian countries studies. Second, to provide a more robust estimation and confront econometrics problem such endogenity, heterogeneity, and cross-country dependency, the this study opts the newly developed Dynamic Common Correlated Estimators of Chudik and Pesaran (2015). The employment of this estimator provides a novelty contribution as previous empirical works failed to consider the heterogeneity that exists among Asian countries. Third, this study also sheds light on the industrial and services effects on CO_2 emissions and provide a direction in preparing a workable policies to combat the pollution emissions. Thus, this study aims to contribute to the empirical evidence by examining the expansion effects of industrial and service sector on the carbon emissions in the non-linear framework for 34 selected Asian countries from 1990 to 2016.

Further, the second section presents the review of several past empirical studies related this current study, the third section highlighted the model specification and proposed estimator, the fourth section exposes the empirical results and finding, and the last section discussion of the finding as well as conclusion.

Literature Review

Most studies in the field of sectoral composition and pollution nexus majority focused on industrialization effects. Cherniwchan (2012) for instance, adopted a two-sector model of neoclassical growth in a small open economy using sulphur emissions data for 157 countries over the period 1970-2000. His study concluded that the industry has positively influenced the emission changes where it empirically indicated that a 1 per cent raise in the share of output is in line with an 11 per cent rise in the level of pollution emissions. On the other hand, Alam (2015) found that the shift from the secondary to the tertiary sector does not lead to CO_2

emissions reduction rather increase with rising income. Meanwhile, Akin (2014) and Li *et al*. (2015) believed that the impact of industrialization varies with countries' income levels. Using the STIRPAT framework, they have found out that only in the middle and low-income group, industrialization process have a significant impact toward the CO_2 emissions, while have an insignificant impact on the high income group.

More recent study conducted by Sohag *et al*., (2017) examined the role of sector value addition to GDO on CO_2 emissions for middle income countries. They adopted heterogeneous panel estimators; the Cross Correlated Effect Mean Group (CCEMG) and the Augmented Mean Group (AMG) estimators that relax the assumption of cross-dependence and found out that the agriculture GDP and industrial GDP are positively related with CO_2 emissions. Nevertheless, services sector is positively related with CO_2 emissions in upper middle-income countries but negatively related with CO_2 emissions in lower middle income group. The moderating effect of services sector also found in Asian countries (Yassin & Aralas, 2017)

To date, studies that assess the nonlinear relationship between sectoral composition and pollution only is extremely limited. Based on our limited knowledge, only Taghvaee and Parsa (2015) extended the sectoral composition-pollution nexus in non-linear estimations for a single country, specifically Iran. In their study, is a clearly an N-shaped relationship between manufacturing-pollution nexus, as well as the services-pollution nexus.

In sum, although Sohag *et al*., (2017) overcome the problem of cross-sectional bias and consider heterogeneity, nevertheless the dynamic nature of CO_2 emissions as well as the non-linear relationship in been taken into consideration. Meanwhile, Taghavaee and Parsa (2015) have only limited into single country study. Thus, the global effect of CO_2 Emissions are not taken into account.

Model Construction and Data

This study estimates the sectoral effects of industrial and services on carbon emissions based on the Stochastic Impacts by Regression of Population, Affluence and Technology (STIRPAT) which extended from the IPAT equation by Ehrlich and Holdren (1971). The STIRPAT model specifies as below:

$$I_{it}=a_i P_{it}^{b} A_{it}^{c} T_{it}^{d} e_{it} \tag{1}$$

Where, I_{it} denoted the CO_2 emissions, P_t represent the population effects, A_t denoted the affluence effect, T_t represent the technological effect, and e_{it} is the error term. In panel setting, countries are denoted by the subscripts i (=*1,….,N*) and the subscripts t (t=1,….,T) represent the year; a_i denote the country-specific effect and e_{it} represents the random error term. This study decomposed the affluence effect which generally proxies by GDP per capita such as Sadorsky (2014) with two main sectors; Industrial and services value added. Taking natural logarithms of equation (1) with inclusion on square and cubic term of industrial value added provides a non-linear specification in dynamic panel and is designated as **Model 1.**

$$\mathrm{InCO2_{it}} = \beta_0 \mathrm{InCO2_{it-1}} + \beta_1 \mathrm{lnU_{it}} + \beta_2 \mathrm{Inindu_{it}} + \beta_3 \mathrm{lnindu_{it}}^2 + \beta_4 \mathrm{lnindu_{it}}^3 + + \beta_5 \mathrm{T_{it}} + \lambda_i f_t + \varepsilon_{it} \tag{2}$$

We augment equation (2) with inclusion on square and cubic term of services value added provides a non-linear specification in dynamic panel which designated as **Model 2**.

$$\mathrm{InCO2}_{it} = \beta_0 \mathrm{InCO2}_{it-1} + \beta_1 \ln U_{it} + \beta_2 \mathrm{Inserv}_{it} + \beta_3 \mathrm{lnserv}^2 + \beta_4 \mathrm{lnserv}_{it}{}^3 + +\beta_5 T_{it} + \lambda_i f_t + \varepsilon_{it} \quad (3)$$

In model 1, the population effect proxy by shares of the urban population in second term expected to have a positive relationship with CO_2 emissions (Guo et al., 2016). The second, third, and fourth terms represent the industrial, square value of industrial, and cubic value of industrial value added. While the fifth terms term in both model represent the energy used per unit of output, or energy intensity as proxy for the technology (T) effect. It is expected that the energy intensity is positively influence the CO_2 emissions and enhancement in the efficiency of energy use, it is expected to moderate the growth CO_2 emissions (Shahbaz *et al*., 2016). In model 2, the second, third, and fourth terms represent the services, square value of services, and cubic value of services value added. The industrialization expected to will increase the CO_2 emissions, while the teritarization may lower CO_2 emissions. Further, it is expected that the expansion of industrial sector will intensifies the carbon emissions, while the expansion of services sector will abating the carbon emissions (Alam, 2015). Due to the fact that the CO_2 emissions has a dynamic effects and heterogeneity across Asian countries, the above equations include a pervious value of CO_2 emissions and vector of slope coefficients as heterogeneous across N. Thus, the error term (e_{it}) capturing the unobserved country specific effect (f_t) that includes the individual heterogeneity factor loadings (λ_i) and the remaining disturbance term (ε_{it}).

This study opt the variables in two sources: first, the carbon emissions (CO_2) per capita in metric tons adopted from the Emissions Database for Global Atmospheric Research (EDGAR). Second, the independent variables decomposed into the three effects, namely affluence effect which decomposed into industrial[1] and service value added[2], population effect proxy by the share of urban population, and technology affect denoted by the energy intensity where it often expressed as total energy use per dollar income. All independent variable adopted from the World Development Indicator (2018) dataset from 1990 to 2016.

Dynamic Common Correlated Effects (DCCE)

To estimate both model, the employment of Dynamic Common Correlated Effects (DCCE) model developed by Chudik and Pesaran (2015) will address the unknown types of error cross section dependence due to the presence of common shocks, interdependencies such as trade activities, the heterogeneity among countries, and the endogeneity problem. According to Chudik and Pesaran, the estimator becomes more consistent if $\sqrt[3]{T}$ a lag of cross-section means is added. For a clear explanation, lets the model simplify as follow:

$$y_{it} = \alpha_i + \lambda_i y_{it-1} + \beta_i x_{it} + \sum_{l=0}^{pT} \delta'_{il} \bar{z}_{t-1} + \varepsilon_{it} \quad (4)$$

Where:

$\bar{z}_t = (\bar{y}_t, \bar{y}_{t-1}, \bar{x}_t)$

[1] represents a country's industrial activities such as mining, quarrying, manufacturing, construction, and electricity, gas and water

[2] Represent a country's services activities such as transport, communications, retail trade, banking, insurance public administration, and others services

pT −The number of lags (pT=$\sqrt[3]{T}$)
λ_i − Individual heterogeneity factor loadings
β_i −The heterogeneous coefficient and randomly distribute around common mean, $\beta_i = \beta + \nu_i, \nu_i \sim IID(0, \Omega_V)$

From equation 4, λ_i and β_i are stacked into $\pi_i = (\lambda_{it}, \beta_i)$. The mean group coefficient estimates as in equation 5:

$$\hat{\pi}_{MG=}\tfrac{1}{N}\textstyle\sum_{i=1}^{N}\hat{\pi}_i \quad (5)$$

Where the $\hat{\pi}_i$ and $\hat{\pi}_{MG}$ are consistently estimated with convergence rate $\sqrt{N}$ if $(N, T, pT) \Rightarrow \infty$.
Under the full rank of factor loading, the asymptotic variance can be consistently estimated by:

$$Var(T_{MG}) = N^{-1}\textstyle\sum_{\pi}^{\wedge} = \frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{\pi}_i - \hat{\pi}_{MG})(\hat{\pi}_i - \hat{\pi}_{MG})' \quad (6)$$

The mean group estimates have the following asymptotic distribution (Chudik & Pesaran, 2015):

$$\sqrt{N}(\hat{\pi}_{MG} - \pi) \xrightarrow{d} N(0, \textstyle\sum_{MG}) \quad (7)$$

Results
Initial step is to observed the trends that affected the data, using the Pesaran (2007) CIPS unit root test. The unit root test presented in table 1 shows that all are stationary for all series including with trends-stationary process. This results implied that any possible shock affecting the series is only a temporary effect. Hence, we can proceed with the estimations.

Table 1: Panel Unit Roots Test based on Pesaran (2007)

Variable	CIPS	
	Without Trend	With Trend
$\ln CO_2$	-1.330**	-1.877**
Urbanization(U)	-2.222**	-1.964**
Technology Effect (lnT)	-2.117**	-2.819***
Industrial Value Added (lnindu)	-1.773**	-2.263***
Services Value Added(lnser)	-2.423***	-3.053***

Notes: CIPS test developed with the command of xtcips of stata 14 with 3 maximum lags; the critical value for CIPS statistics at (***) 1 percent, (**) 5 percent, and (*) 10 percent level. The null hypothesis is that the variable is homogeneous non-stationary.

The estimation results in table 2 focused the expansion industrialization effect on the CO_2 emissions in the STRIPAT non-linear model. At first, the lagged value of CO_2 emissions coefficients is positively associate with the current value of CO_2 emissions levels. Next, the estimated coefficient of industrial value added found positively affect the CO_2 emissions for all estimators and implied that a 1 per cent increase in industrial value added significantly increase the CO_2 emissions by 0.333 to 1.461 per cent. Further, as the industrial output expanded as proxy by square term of industrial value added, the CO_2 emissions intensifies by 0.1303 to 0.3920 per cent in 1 per cent increase of industrial value added. Further, at a more high industrial output, the CO_2 emissions still intensifies and show that a 1 per cent increase in square term of industrial will increase the CO_2 emissions by 0.0833 to 0.1122 per cent. The finding provides a monotonic linearity association between industrial and CO_2 emissions.

On the other hand, the services output found to positively relate to CO_2 emissions and indicated that an increase of 1 per cent of services value added will surge the CO_2 emissions by 0.060 to 0.0855 per cent. Meanwhile, the urbanization and energy intensity are positively statistically significant in influencing the CO_2 emissions. The results demonstrated that as share of urban population rise by 1 per cent, it will intensifies the CO_2 emissions by 0.1618 to 0.1743 per cent and 1 per cent increase in energy intensity cause a hike by 0.1358 to 0.4211 per cent in the level of CO_2 emissions. The Jackknife bias correction and Recursive mean adjustment methods that consider the small sample size produce consistent results with the mean group-DCCE. Finally, the CD statistics shows that the result shows that error terms are weakly cross sectional dependence and the value of goodness-of-fit measures (R-square) for all model indicates the model explains approximately 79 to 83 per cent.

Table 2: Result of Heterogeneous Estimation for non-Linear Dynamic STRIPAT Model (Model 1)

Dynamic Common Correlated Effects (DCCE)			
	Mean Group (MG)	Jackknife Bias Correction	Recursive mean adjustment method
$CO2_{it-1}$	0.0526** (0.0784)	0.1023** (0.0564)	0.1191** (0.1810)
Industry Output(Indu)	1.4613** (1.494)	0.8520** (0.4130)	0.3330** 0.1570
Services Output (Serv)	0.0060* (0.0049)	0.0070* (0.0034)	0.0855* (0.0876)
Urbanization(U)	0.1928* (0.1240)	0.1743* (0.1042)	0.1618* (0.2643)
Technology Effect (lnT)	0.1358* (0.2251)	0.4211* (0.2222)	0.4735 (0.2096)
Square of Industry($indu^2$)	0.3920* (0.5627)	0.3430* (1.2180)	0.1303* (1.4440)
Cubic of Industry ($indu^3$)	0.1039* 0.2266	0.1122* (0.101)	0.0833* (0.1230)
Constant	3.778 (0.631)	0.276 (0.443)	0.2881 (0.4515)
R-squared	0.83	0.79	0.82
CD Statistic	-0.54 (0.587)	-0.25 (0.623)	-0.54 (0.590)
Obs.	884	884	850

Notes: The dependent variable is the carbon dioxide emissions (CO_2). All variables are expressed in natural logarithm (ln). (*) significant at the 10 per cent level, (**) significant at the 5 per cent level, and (***) significant at the 1 per cent level. The analysis use dynamic common correlated effects estimation developed by Chudik and

Pesaran(2015). Figure in parentheses are standard error, Cross Sectional Dependence (CD) test which is p-value and the null hypothesis is that the error terms are weakly cross sectional dependent.

Table 3 shows the inclusion of expansion effects of services value added proxies by the quadratic and cubic term of services value added on the CO_2 emissions. Initially, the services value added found to raise the CO_2 emissions. It is implied that 1 per cent of increase on services value added will increase the current CO_2 emissions by 0.4121 to 0.5907 per cent. At certain threshold, the CO_2 emissions diminishing as the services value added build-up as proxy by the quadratic term. This implied that at higher accumulation of services output, the CO_2 emissions will decrease by 0.0813 to 0.0994 per cent. Nonetheless, the further increase of services output proxy by cubic term confirmed that will turn the CO_2 emissions to rise again. This results confirmed that there exist pattern with an N-shaped curvature between services output and CO_2 emissions. Referring to other determinants, the industrial output increase by 1 per cent, the CO_2 emissions rises by 0.6318 to 0.7442 per cent. Meanwhile, the urban population confirmed to significantly enlarge the CO_2 emissions. The technology effect proxy by the energy intensity and suggesting that consuming more energy per output will result in environmental pollution. The Jackknife bias correction and Recursive mean adjustment methods that consider the small sample size produce consistent results with the mean group-DCCE. Finally, the CD statistics show that the error terms are weakly cross sectional dependence and the value of goodness-of-fit measures (R-square) for all model indicates the model explains 53 to 76 per cent of the cross-country variation.

Table 3: Result of Heterogeneous Estimation for non-Linear Dynamic STRIPAT Model (Model 2)

Dynamic Common Correlated Effects (DCCE)			
	Mean Group (MG)	Jackknife Bias Correction	Recursive mean adjustment method
$CO2_{it-1}$	0.1007** (0.1038)	0.0714** (0.1620)	0.0663** (0.1340)
Industry Output(Indu)	0.7442* (0.5072)	0.7918* (0.6666)	0.6318* (0.8275)
Services Output (Serv)	0.4121* (4.146)	0.5840* (0.1303)	0.5907* (0.0499)
Urbanization(U)	2.3535** (1.899)	1.5110** (0.766)	1.0050** (1.8200)
Technology Effect (lnT)	0.2229 (0.2787)	0.6234 (0.8730)	0.3031 (0.1419)
Square of Industry($indu^2$)	-0.0813* 2.138	-0.0961* (1.324)	-0.0994* (8.694)
Cubic of Industry ($indu^3$)	0.0047* (9.547)	0.0091* (0.0026)	0.0061* (0.2833)
Const	45.80** (22.8)	49.107 ** (18.35)	0.8731** (0.3789)
R-squared	0.70	0.53	0.76
CD Statistic	-2.24 (0.025)	-0.97 (0.33.1)	-1.16 (0.2442)
Obs.	884	884	850

Notes: The dependent variable is the carbon dioxide emissions (CO2). All variables are expressed in natural logarithm (ln). (*) significant at the 10 per cent level, (**) significant at the 5 per cent level, and (***) significant at the 1 per cent level. The analysis use dynamic common correlated effects estimation developed by Chudik and Pesaran(2015). Figure in parentheses are standard error, Cross Sectional Dependence (CD) test which is p-value and the null hypothesis is that the error terms are weakly cross sectional dependent.

Conclusion

This study provides an empirical evidences on the roles of industrial and services sectors in influencing the CO_2 emissions. Specifically, this research aims to assess whether the de-industrialization and the movement of services sector can become the solution of environmental problem in Asian countries. This study employs the non-linear STRIPAT model as its analytical framework and estimates the model using the Dynamic Common Correlated Effects (DCEE) estimators which accounts for heterogeneity across countries.

In this study, we disentangle the affluence effects into different sectoral compositions which proxies by industry and services value added. In the first stage, the industrial and services sector found to have a positive effect the carbon emissions in Asian Countries. Alternatively, the industrial sectors of the economy is contributing greatly to carbon emissions compare to the services sectors which slightly different compared to the recent study by Sohag *et al*., (2017) which argue that the services sector has a greater impact on carbon emissions compare to other sectors. Further, with the inclusion of quadratic and cubic terms of industrial output in model 1, the result found that the positive impact of industrial output on CO_2 emissions is permanent. On the other hand, the inclusion of the square term of services, value added confirmed the inverted-U shaped relationship between the services value added and CO_2 emissions, but at certain threshold, finally the CO_2 emissions will bounce back as the shares of services sector enlarge. The possible explanations of the results that the expansion of services sector may enlarge the environmental-friendly services based activities. For instance the eco-tourism and conservations as subsectors of services (Prieur, 2009). Nonetheless, improper planning in the service sector with less emphasis on the employment of clean environment will only intensify the pollution emissions later (Effiong, 2018). Moreover, according to Clemes *et al*., (2003), as the services sector expands, it will encourages the expansion on the industrial sectors as well as the agriculture sector. Turning to the urbanization effect on CO_2 emissions, according to Wang *et al*., (2017) the growth in urbanization in Asian Countries contributes to the pollution intensify due to the vast uses of energy, vehicles, and constructions that emitted emissions. The findings of this study are consistent with Poumanyvong and Kaneko (2010) and Wang *et al*., (2016). Next, similar to the previous studies such as Ameer and Munir (2016), the technology effect proxy by energy intensity is positively related with CO_2 emissions, thus implied that the environmental degradation will become worse, if the economic activities are energy-inefficient

Several policy implications were identified through this study. First, Asian Countries unable to reduce its carbon emissions if focusing with the conventional industrial production. According to Lu *et al*., (2015), the industrial sector should reduce the size of the most pollution industrial sub-sectors. Second, the inverted U-shaped between services sector and carbon emissions suggested that Asian countries with a lower level of services share should speed up the process of tertiarization, however, is should be accompanied with a strategic planning on managing the long-term effects of services sectors and sustainable solution to environmental pollution. Third, policy maker should take extra attention to the over-concentration in the largest city, thus, a proper design and planning for sustainable lifestyles for urban population is needed in Asian countries and encourage the development activities that not only contributes to the economic growth but also reducing the carbon footprint such as eco-tourism and renewable energy consumption in long-run. Fourth, continuous effort in discouraging the high energy extensive-activities and shift to much more eco-friendly need to be done by imposing to the price of carbon emissions either through taxes of cap as proposed by several studies such as (Sadorsky, 2014).

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