Int. J. Econ. Environ. Geol. Vol. 10 (1) 64-69, 2019

Journal home page: www.econ-environ-geol.org

Open Access

ISSN: 2223-957X

Forecasting Carbon Dioxide Emission of Asian Countries Using ARIMA and Simple Exponential Smoothing Models

Samreen Fatima[1]*, Sayed Saad Ali[1], Syeda Sadia Zia[2], Ehtesham Hussain[1], Tayyab Raza Fraz[1], Mehwish Shafi Khan[2]

[1]Department of Statistics, University of Karachi, Pakistan
[2]Department of Mathematics, University of Karachi, Pakistan

*Email: samreen@uok.edu.pk

Received: *13 March, 2019* ***Accepted:*** *17 April, 2019*

Abstract: Industrial revolution has increased the level of pollution due to emission of carbon dioxide in the past few decades. Resulting changes in the world's climate are seen in the form of an increase in temperature which causes heat waves, diseases related to skin, cardiovascular and other respiratory illnesses in humans. According to a past study, overall contribution of continent Asia is 49% - 50% in the production of carbon dioxide. Therefore, data of carbon dioxide emission, heat and electricity, manufacturing industries, residential and commercial buildings, transport and other sources of Asian countries namely: Japan, Bangladesh, China, Pakistan, India, Sri Lanka, Iran, Singapore, and Nepal from 1971 to 2014 have been taken for the present study. Empirical analysis shows that heat and electricity are the main cause to increase carbon dioxide emission in Pakistan, Bangladesh, India, Iran and Sri Lanka. Whereas this emission is increased in China due to residential and commercial buildings and transport variables. On the other hand, for Nepal and Singapore, these variables do not play any significant role in CO_2 emission. Simple exponential smoothing (SES) and ARIMA models are used to forecast CO_2 emissions. Furthermore, simple exponential smoothing is found appropriate for Pakistan and Sri Lanka based on the minimum FMAE. Whereas, for Japan, China, India, Iran and Singapore, ARIMA model is found suitable as it has minimum FMAE value. In Nepal and Bangladesh, both models have significant differences, so any one of them can be used for forecasting.

Keywords: Simple exponential smoothing, carbon dioxide (CO_2), multiple linear regression.

Introduction

Carbon dioxide is produced naturally in the atmosphere but human activities aggravate the process. One of the significant human activities is greenhouse gas emission consisting of several components including water vapor, methane, ozone, nitrous oxide, and halocarbons. Greenhouse gases have the ability to grip and release the infrared radiation in the wavelength range releases from earth, which is necessary to make our planet a comfortable place to live. Because of the phenomenon, the emission of CO_2 level is increasing day by day. According to environmental research, in 1960 CO_2 level was about 270 (ppm) but it reached at 405 (ppm) in 2017. CO_2 is not only affecting the atmosphere but, it has also made the oceans about 30% extra acidic causing increase in sea acidification due to which a large number of sea organisms have been affected (Quere et al., (2016). CO_2 is able to absorb more heat as compared to other greenhouse gases, so the concentration level of carbon dioxide increases in the atmosphere resulting in global warming. Natural disasters such as drought, hurricanes, and storms are more likely to occur as a result of global warming. On the other hand, numerous kinds of species which live in the cold environment are in the danger of going extinct due to melting of glaciers.

Since the mid 17th century, due to Industrial revolution, human activities have altered the balance of the greenhouse gases. Whenever, the economy develops, more carbon dioxide is emitted perhaps because of the increasing number of industrial activities without applying environment friendly systems. There is abundant literature discussing the relationship between economic growth, energy and CO_2 emissions (Arouri et al., 2012; Bartleet and Gounder, 2010; Menyah and Wolde-Rufael, 2010; Niu et al., 2011. Besides these, other factors which may increase CO_2 emissions are urbanization, increase in population, financial development, capital stock and labor force. The relationship between growth in per capita income and CO_2 emissions of 77 non-OECD countries was analyzed by (Aslanidis and Iranzo, 2009). The study of CO_2 emissions due to the transport sector in regional perspective in China was discussed by Zhang and Nian (2013) to model and forecast univariate series of CO_2 emission employing various time series methods (Meng and Niu, 2011; Silva, 2013). In multivariate framework, co-integration method was used to describe the relationship between economic growth per capita, energy consumption and CO_2 emissions (Pao and Tsai, 2010; Liu and Shen, 2011; Muhammad et al., 2011). Effect of economic growth on CO_2 emission using the dynamic panel threshold framework of a panel of 31 developing countries of Asia has been discussed by Aye and Edoja (2017). In another paper, Jamel and Derbali (2016) discusses the influence of energy consumption and economic growth on environmental degradation due to CO_2 emissions. The association between economic growth, urbanization, financial development and electricity consumption in

Copyright © SEGMITE

the United Arab Emirates covering the period (1975–2011) was studied by Sbia, et al. (2017). It was emphasized further by Zhang and Lin (2012) that urbanization plays an important role in energy consumption and CO_2 emissions. In brief, there are many factors, which are affecting the environment by aggravating emission of CO_2.

The main objective of this study is to investigate empirically how heat and electricity, manufacturing industries, residential and commercial buildings, transport and other sources (OS) lead to increase in CO_2 emissions in nine Asian countries during the period from 1972 to 2014. Furthermore, the study focuses on summarizing all the variables through multiple regressions and measures the percentage of variation in CO_2 emissions due to considered variables. Moreover, modeling and forecasting emission of CO_2 by using ARIMA and SES models is done in this manner. Furthermore, this study will be helpful for the policy makers, researchers and environmentalists in taking steps to minimize global warming by emphasizing environment friendly systems in order to reduce carbon dioxide emission.

Materials and Methods

Statistical analysis is a powerful tool for assessing data and providing future estimations using following approaches.

Multiple Linear Regressions

Multiple linear regression is a statistical model, which was first used by Pearson (1908) to know the relationship between several exogenous variables and a single endogenous variable. Mathematically, this relationship can be described as

$$Y_t = a + b_1 x_1 + b_2 x_2 + b_3 x_3 + ... + b_k x_k + \varepsilon_t$$

Where, x_i's are the exogenous variables, Y_t is endogenous, a, b_1,., b_k are regression coefficients and ε_t is error term.

In this study, log-log multiple regression model is used for CO_2 emission, as the relationship between dependent and independent variables is nonlinear hence log transformation is taken. The multiple log-log linear regression model is defined as:

$$\log(CO_2) = \beta_0 + \beta_1 \log(HE) + \beta_2 \log(MI) + \beta_3 \log(RCB) + \beta_4 \log(T) + \varepsilon_t$$

R^2 (coefficient of determination) measures percentage of variance in CO_2 emission by the selected exogenous variables.

Auto Regressive Integrated Moving Average (ARIMA) Model

In statistical modeling, univariate time series model requires only historical data for the variable of interest to forecast. Box-Jenkins ARIMA (Bowden and Payne, 2008) and Pappas, et al., 2008) is commonly used for modeling and forecasting environmental, financial, energy and engineering data.

A time series model in which the current value of the series of interest is the linear aggregate of its own past values of the series of interest and a random disturbance (ξ_t) is called Autoregressive (AR) model. An autoregressive process of order p is mathematically described as:

$$z_t = k + \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_p z_{t-p} + \xi_t$$

$$z_t = k + \sum_{i=1}^{p} \phi_i \ z_{t-i} + \xi_t \text{ ....(1)}$$

Where Equation (1) is called AR (p) process, z_t is time series data, 'p' is the order, 'k' is an 'intercept parameter' that is related to the mean of z_t. ϕ_i's unknown autoregressive parameters and ξ_t is assumed to be uncorrelated random variables with zero mean and variance σ_ξ^2.

On the other hand, a moving average (MA) term in a time series model is a sum of weighted past error. Where MA (q) present 'q' order moving average process is written as:

$$z_t = b + \alpha_1 \xi_{t-1} + \alpha_2 \xi_{t-2} + ... + \alpha_q \xi_{t-q} + \xi_t$$

$$z_t = b + \sum_{j=1}^{q} \alpha_i \ \xi_{t-i} + \xi_t \text{ ....(2)}$$

'b' is a constant, $\alpha_i \geq 0$ are unknown parameters (MA coefficients) and ξ_t white noise disturbance term.

An ARMA model is the sum of an Autoregressive and Moving Average processes proposed by Box and Jenkins, (1976). Mathematically an ARMA model is defined by the following equation,

$$z_t = C + \sum_{i=1}^{p} \phi_i \ z_{t-i} + \sum_{j=1}^{q} \alpha_i \ \xi_{t-i} + \xi_t \text{ .... (3)}$$

One extension to the ARMA (p, q) class of processes which greatly enhance their value as empirical descriptors of non-stationary time series is the class of autoregressive–integrated-moving average. The number of times 'd' that the integrated process must be differentiated to make stationary is said to be the order of the integrated process and is called an autoregressive–integrated-moving average, ARIMA (p, d, q) process. Model building process of an ARIMA model includes, estimation and diagnostic checking and forecasting.

Simple Exponential Smoothing (SES) Model

Simple exponential smoothing (SES) model also belongs to a family of univariate time series model used to forecast business, financial and economic data. SES provides the optimal forecasts for a random walk plus noise (Muth, 1960). It is a weighted linear sum of recent past observations or lags.

Let $z_1, z_2, \ldots, z_n$ be a time series, the simple exponential smoothing equation is defined as:

$$F_{t+1} = \lambda z_t + (1-\lambda)F_t$$

Above equation can be written as follows:

$$F_{t+1} - F_t = \lambda(z_t - F_t)$$

$$F_{t+1} = \lambda\xi_t + F_t \ldots\ldots\ldots\ldots\ldots(4)$$

Where z_t is a series under consideration, λ is smoothing parameter (weight), ξ_t is called error and F_t and F_{t+1} are the forecasted values at t, and t+1 respectively. The value of the λ lies between, $0 < \lambda < 1$.

Using recursive method, the general form of the equation (4) is given below:

$$F_{t+1} = \lambda\sum_{i=0}^{t-1}(1-\lambda)z_{t-i} + (1-\lambda)z_t \ldots\ldots\ldots(5)$$

In Equation (5), weights exponentially decline towards zero and thus the name is simple exponentially smoothing. The decay is slow for small values of λ, so rate of decay can be controlled by selecting an appropriate value of λ.

Data Analysis

This study uses annual data of nine Asian countries on carbon dioxide (metric ton per capita) emission, heat and electricity (HE), manufacturing industries (MI), residential and commercial building (RCB), transport (T) and other sources (OS) covering the period from 1972 to 2014. Data were collected for Japan, Nepal, Bangladesh, China, Pakistan, India, Sri Lanka, Iran and Singapore from World Bank official website www.worldbank. org.

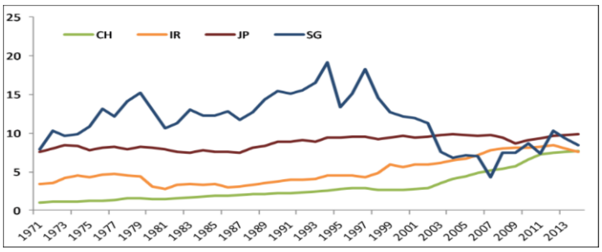

Fig. 1(a) Carbon dioxide emissions of nine Asian countries between 1971-2014.

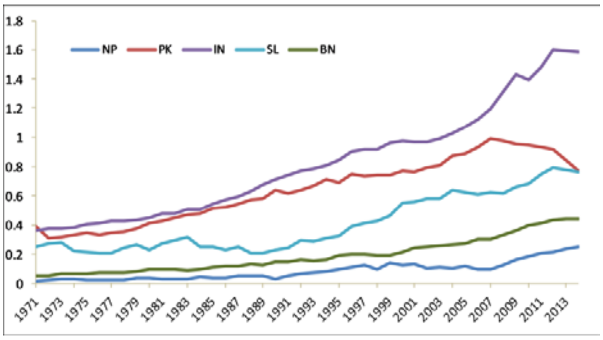

Fig. 1 (b) Carbon dioxide emissions of nine Asian countries between 1971-2014.

(Figs. 1a, b) show a time series plot of CO_2 emission data of nine Asian countries. Figure 1a reveals that China, Iran, Japan and Singapore are prominent peak countries. Whereas, Figure 1b shows that countries like Nepal, Pakistan, Bangladesh, India and China are lying at the bottom. Graph shows that Singapore has relatively large and small peaks and exhibits no clear pattern. It increases from 1971 to 1997 and attains maximum value i.e. 19.11 in 1994 after which it has a decreasing trend till 2007 and reaches at a minimum value i.e. 4.34 in 2007 Figure 1a. Whereas, China and Iran have parabolic trend but Japan has a wiggly linear trend. Moreover Pakistan, India, Sri Lanka, Nepal and Bangladesh display slow increasing trend (Fig. 1b).

Table 1. Descriptive statistics of nine Asian countries.

Country	BN	CH	IN	IR	JP	NP	PK	SG	SL
Mean	0.185	2.911	0.637	5.014	8.74	0.083	0.637	11.662	0.398
Med	0.153	2.314	0.641	4.51	8.873	0.067	0.641	12.167	0.298
Max	0.439	7.551	0.995	8.454	9.909	0.234	0.995	19.119	0.794
Min	0.052	1.042	0.309	2.808	7.411	0.016	0.309	4.343	0.205
SD	0.111	1.83	0.219	1.732	0.819	0.058	0.219	3.286	0.189
Range	0.387	6.509	0.686	5.647	2.498	0.217	0.686	14.776	0.59

Notes: Max= Maximum, Min=Minimum, SD= Standard deviation, R=Range and JB is Jurka Bera test. Japan (JP), Bangladesh (BN), China (CH), Pakistan (PK), India (IN), Sri Lanka (SL), Iran (IR), Singapore (SG) and Nepal (NP)

Descriptive statistics of CO_2 emission for all selected countries are presented in Table 1. Findings demonstrate that Singapore has the highest average value i.e. 11.66 whereas, Nepal has the lowest value i.e. 0.83. Moreover, Singapore exhibits high volatility with standard deviation 3.286 and range 14.776. On the contrary, Nepal has low variation because both standard deviation and range are at a minimum.

Correlations are computed in order to find which variable has high/low correlation with CO_2. Table 2 displays a very high positive correlation coefficient between CO_2-HE of Pakistan, Bangladesh, India, Iran, and Sri Lanka. Moreover, the pair of correlation CO_2-RCB is high for China but the pair of CO_2-T is high for both China and Sri Lanka. Whereas, the pairs of correlation of CO_2 and selected variables, which has minimum or negative value indicates that CO_2 emission is not much affected by these variables.

However, in Japan no pair of correlation is highly significant.

Table 2. Simple correlation coefficients of Asian countries.

JP							PK							BN						
	CO_2	HE	MI	RCB	T	OS		CO_2	HE	MI	RCB	T	OS		CO_2	HE	MI	RCB	T	OS
CO_2	1						CO_2	1						CO2	1					
HE	0.56	1					HE	0.88	1					HE	0.83	1				
MI	-0.8	-0.7	1				MI	-0.6	-0.8	1				MI	-0.6	-0.9	1			
RCB	-0.8	-0.6	0.86	1			RCB	-0.8	-0.8	0.64	1			RCB	0.39	0.67	-0.9	1		
T	0.7	0.26	-0.8	-0.8	1		T	-0.9	-1	0.69	0.86	1		T	-0.9	-0.9	0.76	-0.6	1	
OS	0.61	0.1	-0.8	-0.7	0.89	1	OS	0.48	0.47	-0.7	-0.8	-0.6	1	OS	0.26	0.4	-0.7	0.81	-0.5	1
CH							IN							NP						
CO_2	1						CO_2	1						CO_2	1					
HE	-0.9	1					HE	0.85	1					HE	-0.6	1				
MI	-0.9	0.82	1				MI	-0.8	-1	1				MI	0.02	-0.3	1			
RCB	0.9	-0.8	-1	1			RCB	-0.2	0.08	-0.2	1			RCB	-0.3	0.3	-0.6	1		
T	0.97	-0.9	-1	0.93	1		T	-1	-0.9	0.82	0.19	1		T	0.5	-0.3	-0.5	-0.3	1	
OS	-0.9	0.76	0.7	-0.7	-0.8	1	OS	T01	-0.7	-0.9	0.88	-0.3	1	OS	0.06	-0.4	-0.6	0.09	0.65	1
SL							IR							SG						
CO_2	1						CO_2	1						CO_2	1					
HE	0.93	1					HE	0.92	1					HE	0.63	1				
MI	-0.7	-0.6	1				MI	-0.7	-0.7	1				MI	-0.7	-0.8	1			
RCB	-0.8	-0.8	0.73	1			RCB	-0.9	-0.9	0.65	1			RCB	-0.2	0	0.19	1		
T	0.7	0.57	-0.8	-0.9	1		T	-0.4	-0.5	-0.2	0.31	1		T	0.18	-0.1	-0.4	-0.3	1	
S	-0.5	-0.7	-0.1	0.04	0.09	1	OS	0.32	0.15	-0.7	-0.2	0.15	1	OS	-0.1	-0.5	-0.1	-0.2	0.38	1

Furthermore, a statistical method called multiple regression is used to summarize these variables. The output of multiple regressions is given in Appendix 1.

R-squared (R^2), a statistical measure which is calculated to explain the percentage of variation in CO_2 emission due to HE, MI, RCB, T and OS is reported in Table 3. Empirical analysis shows that Pakistan, Bangladesh, China, India, Sri Lanka and Iran have above 90% variation, whereas in Singapore, Nepal and Japan 75% -77% variation is explained by selected variables. Moreover, Singapore has very low value of R^2 i.e. 54.19% showing variation that is explained via selected variables and 45.81% is unexplained variable due to other reasons.

Table 3. Coefficient of determination (R-Squared in %).

Country	JP	PK	CH	IN	SL	IR	SG	NP	BN
R-Squared %	77	97.2	91	98.3	96.4	90.2	54.2	75	90.2

In order to forecast CO_2 emissions ARIMA model is used. Stationary is one of the key concepts of time series modeling. Therefore number of time difference is taken for each CO_2 emission series to make them stationary. Unit root test is applied to make CO_2 emissions series stationary. Table 4 shows P-value is at less than at 5% level of significance so null hypothesis (data is non-stationary) is rejected. Data for Pakistan, China and India became stationary on second difference while the rest of countries are stationary at first difference.

Table 4. Unit root test for CO_2.

Country	JP	PK	CH	IN	SL	IR	SG	NP	BN
Difference	1	2	2	2	1	1	1	1	1
P-Value	0	0	0	0	0	0	0	0	0

In statistical modeling, the developed model must be parsimony (less number of parameters) because larger number of coefficients decrease degree of freedom and make model less-parsimony. In order to develop ARIMA model, the data are divided into model building period consisting of 1971 to 2010 and validation period is from 2011 to 2014. A number of different orders of ARIMA models are developed such that '$p \leq 2$', and '$q \leq 2$', suitable model of each country is selected based on AIC. Table 5 reports AR (1), MA (1) and MA (2) follow (China and Japan), (Pakistan and India) and Iran correspondingly. Furthermore, Nepal and Bangladesh have ARIMA (1,1,1) model but Singapore and Sri Lanka (2,1,2) is found to be a suitable model as the AIC is minimum. Therefore, above selected models are used to forecast CO_2 emissions of each country using data from 2011 to 2014.

In the next step SES model has been used for forecasting CO_2 emission. This method depends on smoothing parameter and the selection of an appropriate value of λ which is very crucial. Therefore, choosing smoothing parameter is basically a trial and error method. Different values of λ are chosen such as λ = 0.45, 0.55 and 0.65. From all, λ = 0.65 is found to be the most appropriate value. Moreover, FMAS are then computed for each country. Forecast mean absolute error (FMAE) for the period 2011-2014 using ARIMA and SES have been computed shown in Table 6. Furthermore, FMAE were represented as a bar graph (Fig. 2).

Table 5. AIC of ARIMA models.

Country	AR(1)	AR(2)	MA(1)	MA(2)	ARIMA(1,1)	ARIMA(2,2)
CH	*-3.27	-3.23	-3.26	-3.22	-3.23	-3.12
JP	*-3.6	-3.6	-3.5	-3.5	-3.59	-3.26
PK	-2.96	-2.9	*-2.96	-2.9	-2.93	-2.86
IN	-3.8	-3.77	*-3.9	-3.29	-3.78	-3.92
SG	-0.46	-0.43	-0.53	-0.48	-0.422	*-0.604
SL	-1.64	-1.56	-1.66	-1.61	-1.59	*-1.98
IR	-1.9	-1.95	-1.99	*-1.99	-1.96	-1.88
NP	-5.51	-5.5	-5.5	-5.5	*-5.52	-5.51
BN	-6.1	-6.08	-6.13	-6.2	*-6.21	-6.2

Notes: *Indicates minimum value of AIC. Where AIC stands Akaike information criterion (AIC= $2m$-2ln (Likelihood function). m is estimated parameter.

Table 6. FMAE of ARIMA and SES models.

Country	JP	BN	CH	PK	IN	SL	IR	SG	NP
ARIMA	0.13	0.07	0.18	0.26	0.4	0.95	0.23	1.06	0.003
SES	0.3	0.06	0.75	0.04	0.62	0.05	0.27	1.12	0.026

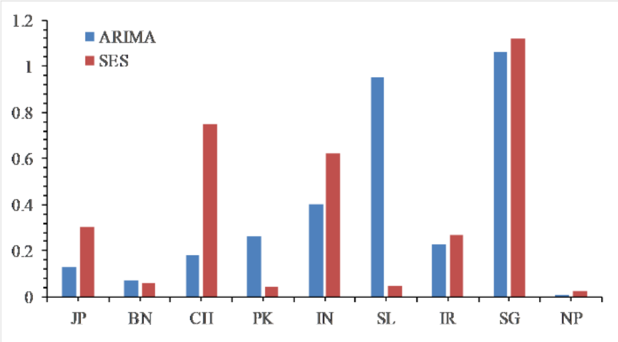

Fig. 2 FMAE of ARIMA and SES models.

Fig. 2 Shows comparison of ARIMA and SES models for all the countries. In Pakistan and Sri Lanka SES models attain minimum FMAE as compared to ARIMA. Whereas, SES model failed to provide better forecast for Japan, China, India, Iran and Singapore because FMAE value is greater as compared to ARIMA process. Furthermore, for Nepal and Bangladesh both models of FMAE are approximately same.

Conclusion

The main aim of the study is to inspect relationship of variables like heat and electricity, manufacturing industries, residential and commercial buildings, transport and other sources (OS) on CO_2 emissions of the selected Asian countries. The result of correlation coefficient (Table 2) revealed that heat and electricity (HE) are the potential variable for emission of CO_2 for Pakistan, Bangladesh, India, Iran, and Sri Lanka. Whereas, in China the variables of residential and commercial building (RCB) and transport (T) have high impact on CO_2 emission. Furthermore, in Singapore and Nepal considered variables have no significant effect on CO_2 emissions. To forecast CO_2 emissions for each country, ARIMA and SES models were used. The data from 1972-2010 were used for model building and 2011-2014 data to assess validity of the model. When comparing FMAE of ARIMA and SES models, it was found that SES model is suitable for Pakistan and Sri Lanka. Whereas, ARIMA model was found appropriate for Japan, China, India, Iran, and Singapore but for Nepal and Bangladesh both models FMAE perform in similar ways.

Result obtained from the empirical analysis show that CO_2 emissions are increasing in most of the countries except for Singapore. For countries like Pakistan, Bangladesh, India, Iran, and Sri Lanka, heat and electricity and for China residential and commercial buildings and transport are the main factors of CO_2 emission. Therefore, low carbon technologies should be installed, especially in countries in which the above-mentioned variables play a strong role in increasing CO_2 emissions. So, necessary policies and actions in the field of control and reduction of the amount of CO_2 will minimize the deterioration of environmental quality which raises concerns about global warming and climate change arising mainly from greenhouse gas (GHGs) emissions.

Table 1. Output of multiple regression analysis.

Country	Variable	Coefficient	Std. Error	t-Statistic	Prob.
JP	C	20.03489	4.966703	4.03384	0.0003
	LOG(HE)	-2.423088	0.678612	-3.570654	0.001
	LOG(MI_C)	-1.531729	0.429159	-3.569145	0.001
	LOG(OS)	-0.162072	0.049161	-3.296767	0.0022
	LOG(RBCP)	-0.755528	0.245044	-3.083235	0.0039
	LOG(T01)	-0.66679	0.273042	-2.442077	0.0195
NP	C	-0.917456	5.011436	-0.183072	0.8557
	LOG(HE)	-0.521396	0.073766	-7.068264	0
	LOG(MI_C)	-0.428049	0.437355	-0.978723	0.3339
	LOG(OS)	0.124384	0.437805	0.284108	0.7779
	LOG(RBCP)	-0.16304	0.673993	-0.241902	0.8102
	LOG(T01)	-0.16304	0.673993	-0.241902	0.8102
PK	C	0.571727	2.277042	0.251083	0.8031
	LOG(HE)	0.189519	0.222208	0.852891	0.3992
	LOG(MI_C)	-0.108475	0.23062	-0.470364	0.6409
	LOG(OS)	-0.183769	0.01835	-10.01458	0
	LOG(RBCP)	-0.540257	0.178714	-3.023019	0.0045
	LOG(T01)	0.049559	0.157449	0.314763	0.7547
SG	C	4.068805	4.338392	0.93786	0.3544
	LOG(HE)	-0.391377	0.893694	-0.437932	0.664
	LOG(MI_C)	-0.287667	0.088223	-3.260686	0.0024
	LOG(OS)	-0.008287	0.170279	-0.04867	0.9614
	LOG(RBCP)	-0.038623	0.080028	-0.482619	0.6322
	LOG(T01)	0.177559	0.217511	0.816325	0.4195
SL	C	5.773403	1.668066	3.461135	0.0014
	LOG(HE)	0.031911	0.084351	0.378312	0.7074
	LOG(MI_C)	-0.180473	0.099442	-1.814852	0.0777
	LOG(OS)	-0.426317	0.086383	-4.935202	0
	LOG(RBCP)	0.065302	0.037759	1.729425	0.0921
	LOG(T01)	-1.359609	0.342486	-3.969828	0.0003
CH	C	-11.78927	6.841058	-1.723311	0.093
	LOG(HE)	1.452971	0.552167	2.631399	0.0122
	LOG(MI_C)	2.346728	1.134741	2.068073	0.0455
	LOG(RBCP)	-0.684308	0.210132	-3.256557	0.0024
	LOG(T01)	0.368909	0.385532	0.956882	0.3447
BN	C	-4.293195	6.705081	-0.64029	0.5259
	LOG(HE)	1.082781	0.874501	1.23817	0.2235
	LOG(MI)	0.558086	0.47525	1.1743	0.2478
	LOG(OS)	0.117527	0.219172	0.536234	0.595
	LOG(RB)	-1.681793	0.482066	-3.488717	0.0013
	LOG(T)	0.559056	0.524336	1.066217	0.2932
IR	C	-16.48991	12.21294	-1.3502	0.1852
	LOG(HE)	2.182555	1.018528	2.142853	0.0388
	LOG(MI_C)	0.74806	0.775877	0.964148	0.3412
	LOG(OS)	-0.153096	0.169655	-0.902394	0.3727
	LOG(RBCP)	0.898467	0.983751	0.913308	0.367
	LOG(T01)	1.926636	1.084292	1.776861	0.0838
IN	C	5.98	2.41	2.48	0.0177
	LOG(SER02)	-0.24	0.34	-0.7	0.4884
	LOG(SER03)	-0.38	0.16	-2.41	0.0207
	LOG(SER04)	-1.41	0.12	-11.7	0
	LOG(SER05)	-0.36	0.23	-1.56	0.1272

References

Afotey, B. N., Sattler, M. L., Mattingly, S. P., Chen, V. C. (2013). Statistical model for estimating carbon dioxide emissions from a light-duty gasoline vehicle. *Journal of Environmental Protection,* **4**, 8-15.

Arouri, M. E. H., Youssef, A. B., M'henni, H., Rault, C. (2012). Energy consumption, economic growth and CO_2 emissions in Middle East and North African countries. *Energy Policy*, **45**, 342-349.

Aslanidis, N., Iranzo, S. (2009) Environment and development: is there a Kuznets curve for CO_2 emissions? *Applied Economics*, **41** (6), 803-810.

Aye, G.C., Edoja, P.E. (2017). Effect of economic growth on CO_2 emission in developing countries: Evidence from a dynamic panel threshold model. *Cogent Economics and Finance*, **5**(1), 1379239 pages.

Bowden, N., Payne, J.E. (2008). Short term forecasting of electricity prices for MISO hubs: Evidence from ARIMA-EGARCH models. *Energy Economics*, **30** (6), 3186-3197.

Box, G. E., Jenkins, G. M. (1976). Time series analysis: Forecasting and control San Francisco. *Calif: Holden-Day*.

Jamel, L., Derbali, A. (2016). Do energy consumption and economic growth lead to environmental degradation ? Evidence from Asian economies. *Cogent Economics and Finance*, **4** (1), 1170653 pages.

Liu, C., Shen, Q. (2011). An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers, Environment and Urban Systems*, **35** (5), 347-357.

Le Quéré, C., Andrew, R. M., Canadell, J. G., Sitch, S., Korsbakken, J. I., Peters, G. P., Keeling, R. F. (2016). Global carbon budget 2016. *Earth System Science Data* (Online), **8** (2).

Meng, M., Niu, D. (2011). Modeling CO2 emissions from fossil fuel combustion using the logistic equation. *Energy*, **36** (5), 3355-3359.

Menyah, K., Wolde-Rufael, Y. (2010). Energy consumption, pollutant emissions and economic growth in South Africa. *Energy Economics*, **32** (6) 1374-1382.

Muth, J.F. (1960). Optimal properties of exponentially weighted forecasts. *Journal of the American Statistical Association*, **55** (290), 299-306.

Muhammad, S.S., Muhammad, Z., Muhammad, S. (2011). Renewable and nonrenewable energy consumption, real GDP and CO2 emissions nexus: a structural VAR approach in Pakistan.

Niu, S., Yongxia, D., Yunzhu, N., Yixin, L., Guanghua, L. (2011). Economic growth, energy conservation and emissions reduction: A comparative analysis based on panel data for 8 Asian-Pacific countries. *Energy Policy*, **39** (4), 2121-2131.

Pao, H.T., Tsai, C.M. (2010). CO_2 emissions, energy consumption and economic growth in BRIC countries. *Energy Policy*, **38** (12), 7850-7860.

Pao, H.T., Fu, H.C., Tseng, C.L. (2012). Forecasting of CO_2 emissions, energy consumption and economic growth in China using an improved grey model. *Energy*, **40** (1), 400-409.

Pappas, S.S., Ekonomou, L., Karamousantas, D.C., Chatzarakis, G.E., Katsikas, S.K., Liatsis, P. (2008). Electricity demand loads modeling using AutoRegressive Moving Average (ARMA) models. *Energy*, **33**(9), 1353-1360.

Pearson, K. (1908). VI. on the influence of double selection on the variation and correlation of two character. *Biometrika*, ***6***(1), 111-112.

Sbia, R., Shahbaz, M., Ozturk, I. (2017). Economic growth, financial development, urbanisation and electricity consumption nexus in UAE. *Economic Research-Ekonomska Istraživanja*, **30** (1), 527-549.

Silva, E.S. (2013). A combination forecast for energy-related CO_2 emissions in the United States. *International Journal of Energy and Statistics*, **1** (4), 269-279.

Zhang, C., Nian, J. (2013). Panel estimation for transport sector CO_2 emissions and its affecting factors: A regional analysis in China. *Energy Policy*, **63,** 918-926.

Zhang, C., Lin, Y. (2012). Panel estimation for urbanization, energy consumption and CO_2 emissions: A regional analysis in China. *Energy Policy*, **49**, 488-498.