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Forecasting CO2 emissions: Does the choice of estimator matter?

Afees A. Salisu[a,d], Lateef O. Akanni[a,b] and Ahamuefula E. Ogbonna[a,c]

[a] Centre for Econometric & Allied Research, University of Ibadan, Nigeria.
[b] Department of Economics, University of Lagos, Nigeria. Email: akanniolat@yahoo.com; Phone: +234(0)8057907425.

[c] Department of Statistics, University of Ibadan, Nigeria.
Email: ogbonnaephraim@yahoo.com; ae.ogbonna@cear.org.ng;
Phone: +234(0)8028856320.

[d]Corresponding Author:
Email: adebare1@yahoo.com; aa.salisu@cear.org.ng;
Phone: +234(0)8034711769.

Abstract

Extant studies in the literature on carbon emissions have done so using numerous methodologies. However, the Environmental Kuznets Curve has remained the workhorse for modelling the link between development and emissions. This study sets out to test the predictability of the EKC hypothesis for CO_2 emissions in the US and consequently offers to answer two key questions. First, does the choice of estimator matter for the predictability of EKC in forecasting CO2 emissions? Second, are the results sensitive to any of the following: measures of CO2 emission and output and multiple forecast periods? The results uphold the stance of the inverted U-shaped relationship postulated by the EKC hypothesis. Also, the choice of estimator matters for accurate forecast performance of EKC for CO2 measures. More importantly, any estimator that ignores the inherent statistical properties of the predictors such as endogeneity, conditional heteroscedasticity and persistence, among others, may produce less desirable forecasts than the time series models. This conclusion is valid regardless of the proxies for CO2 emissions and output.

JEL Classification: C53, Q51
Key words: US, Environmental Kuznets Curve, CO_2 Emissions, Forecast evaluation

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1.0 Introduction

Discussions on global warming and climate change have been on for quite some time. Climate change is an issue that affects everyone in every country on every continent and it has been at the core of discussions at different international fora with legally binding treaties and agreements reached on different occasions. Since the United Nations Framework Convention of Climate Change (UNFCCC, 1992), quite a number of follow up treaties and agreements have been reached towards mitigating the menace of environmental degradation. For instance, the Kyoto Protocol (1995), the Cancun agreements (2010) and lately, the Conference of the Parties (COP 21) held in Paris in 2015, all aim towards the reduction of greenhouse gases (GHG), which is the major cause of climate change.

Notwithstanding the fact that the literature is awash with studies on the role of growth in emissions, as long as the actualization of sustainable development continues to arrest our attention both at the domestic and international levels, the need to deal with emission issues will remain critical. More importantly, the ability to address environmental issues relies essentially on how well we are able to link such issues to growth and development. In other words, the ability to forecast future emissions accurately may engender possible strategies and policies to mitigate the magnitude of such emissions in the future.

Another motivation for a renewed interest in ensuring accurate forecasts of emissions is underscored by the global financial crisis. While the world is gradually coming out of the global economic collapse, the world is and remains on the brink of ecosystem collapse owing to the need for massive investments in the real sector for a faster economic recovery and the consequences of such actions on the environment. Therefore, the analyses and forecast of growth-oriented emissions is of prime importance at this moment.

In the literature, the Environmental Kuznets Curve (EKC hereafter) has remained the workhorse for modelling the link between development and emissions. In fact, studies on the validity or otherwise of EKC are extensive, too numerous to mention, to the extent that there is hardly any country in the world that has not been subjected to EKC hypothesis, whether as a country-specific or panel study. Nonetheless, a review of the literature on EKC is well documented in the following recent papers: Ahmad et al. (2017), Apergis et al. (2017), Atasoy (2017), Özokcu and Özdemir (2017), Gill et al. (2018), Xu (2018) and Zambrano-Monserrate et al. (2018). The EKC hypothesis postulates an inverted U-shaped relationship between the level of environmental degradation and growth in income. After an economy has attained a given growth threshold, further growth in the economy can reduce environmental degradation. At the early stages of growth, primary production dominates and there is abundance of natural resource stock, accompanied by limited waste generation. As industrialisation begins, there is significant resource depletion and increased waste accumulation. During this industrialisation phase, positive relationship is witnessed between income and environmental degradation. However, with further growth, information diffusion and improved technology limit the material basis for an economy and as a result reduce environmental degradation (Panayotou, 2003).

In spite of the wide acceptance and popularity for environmental modelling, the EKC is scarcely used for forecasting purposes (Perez-Suarez and Lopez-Menedez, 2015). More noticeably, the vast literature on EKC focus majorly on impact (in-sample) analyses, while the forecast of emissions has essentially relied on time series models including univariate models (such as the Autoregressive Integrated Moving Average (ARIMA), Autoregressive Fractionally Integrated Moving Average (ARFIMA)), univariate volatility models (such as the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and its variants), and multivariate models (such as the Vector Autoregressive models and Vector Error Correction Models). Other models include the grey models and the artificial neural network, among others (see Perez-Suarez and Lopez-Menedez, 2015 for a review of the forecast-based models for emissions). The few exceptions involving both the in-sample and out-of-sample forecast analyses of emissions using the EKC include Auffhammer et al. (2004), Aldy (2006), Auffhammer and Carson (2008), Halicioglu (2009), Jaunky (2011), Pao and Tsai (2011), Pao et al. (2012) and Perez-Suarez and Lopez-Menedez (2015).

One of the notable shortcomings of most of these time series models is that the role of real economic activity is rarely accounted for in the forecasting process and therefore, the underlying framework is neither influenced by the EKC nor its variants. While some interesting forecast results are usually reported using the time series models, we further attempt to offer new insights into how much of information from the real sector productivity can be exploited to effectively forecast emissions using the EKC. Thus, we demonstrate how the forecasting accuracy of the EKC can be enhanced to produce better forecast results than the time series models, which have been validated as better forecasting tools for emissions. In addition, our approach also differs from studies involving the forecasting of emissions with EKC in the following ways. First, we argue that the choice of estimator matters for forecasting of future trends in emission series. More importantly, we demonstrate that ignoring the underlying statistical properties of the predictors of emissions in the EKC model renders the forecast performance of the curve less optimal to the time series models. Thus, we offer a comparative analysis between the standard approach used in estimating the EKC and the proposed estimator in this study. The estimator, developed by Westerlund and Narayan [WN] (2012, 2015) is particularly suitable for predictive models where the underlying factors are found to exhibit persistence, endogeneity and conditional heteroscedasticity effects.[1] Our preliminary results indicate that the EKC predictors exhibit these effects and that explains why the traditional EKC usually underperforms the time series models. The augmented EKC model that accounts for these effects consistently outperforms other competing estimators as well as the time series models including ARIMA and ARFIMA. Thus, the consideration of real economic activity in the formulation of forecast model for emissions will produce more accurate results than those that ignore it.

The paper is structured into five sections as follows: Section 2 presents a brief review of the literature on the EKC; Section 3 focuses on the methodology adopted including the forecast procedure; some preliminary analyses are provided in Section 4; the results are presented and discussed in Section 5 while the Section 6 concludes the paper.

2.0 A review of the literature on the EKC model[2]

The emergence of the EKC-model in the environment-growth debates marks a major milestone in empirical debates on the relationship between economic growth and environmental quality. The pioneering work by Grossman and Krueger (1991) described the

[1] The application of the WN (2012, 2015) estimator to forecast macroeconomic series is increasingly gaining recognition in the literature owing to its ability to deal with the inherent statistical properties of the predictors in a forecast model and consequently produce superior forecast outcomes. Examples of studies that have employed this approach include but not limited to Makin et al. (2014) Narayan and Sharma (2014), Narayan and Bannigidadmath (2015), Phan et al. (2015), Devpura et al. (2018), Salisu and Isah (2018) and Salisu et al. (2018).

[2] It is important to acknowledge here that papers on emissions are extensive and we do not have the luxury of space to mention all of them in a single paper. However, for a comprehensive review of some of these papers see Bo (2011) and Tiba and Omri (2017).

EKC and its potential implications for formulating policies towards sustainable economic growth. The EKC model postulates an inverted U-shaped relationship between economic growth and the environment. That is environmental pollution increases with income level up to a certain threshold after which it begins to decline.

Using different measures of environmental quality, including water and air, and by collecting data for different economies as well as using different econometric techniques, some of the empirical results in the literature support the validity of the EKC hypothesis (see Grossman and Krueger, 1995; Haisheng et al. 2005; Plassmann and Khanna, 2006; Ang, 2007; Halicioglu, 2009; Ghosh, 2008; Fodha and Zaghdou, 2010; Ozturk and Acaravci, 2010; Iwata et al., 2011; Nasir and Rehman, 2011; Alam et al., 2012; Franklin and Ruth, 2012; Saboori et al., 2012; Ahmed and Long, 2013; Baek and Kim, 2013; Kohler, 2013 and Shahbaz et al, 2014 among others). On the other hand, some studies do not find empirical support for the existence of the EKC (Paudel et al., 2005; Akbostanci et al., 2009; Llorca and Meunié, 2009; Luzzati and Orsini, 2009; Pao and Tsai, 2011; Zhu et al, 2012; Ahmed and Long, 2013; Govindaraju and Tang, 2013; Bölük and Mert, 2014; Robalino-López et al., 2014).

Besides, the EKC hypotheses have been found to also hold for certain measures of pollutants such as sulphur dioxide (SO_2) (see Stern and Common, 2001; Gao et a., 2011 and Arouri et al., 2012), suspended particulate matters (SPM) (see Stern, 1998 and Markandya et al., 2006), and nitrogen dioxide (NO_2) (see Panayotou, 1993; Hill and Magnani, 2002; Archibald et al., 2004; Welsch, 2004; Fonkych and Lempert, 2005; Roumasset et al., 2008; Song et al., 2013; Park and Lee, 2011; and Sinha and Bhattacharya, 2016). However, the test for EKC using carbon dioxide (CO_2) emissions as a measure of pollutant is the most prominent and have generally produced diverse findings in the empirical literature (Onafowora and Owoye, 2014). Studies such as Shafik and Bandyopadhyay (1992), Grossman and Krueger (1995), Coondoo and Dinda (2002), Apergis and Payne (2010) and Narayan and Narayan (2010) alongside several others find evidence of an inverted U-shaped relationship between CO_2 emissions and income growth. On the other hand, studies such as the Shafik (1994), Akbostanci et al. (2009), Ozturk and Acaravci (2010) and, Pao and Tsai (2010) do not support the EKC. We however argue in this paper that the conflicting results in the validation of EKC may be due to the choice of methodology and the behaviour of the underlying variables of the curve. This is the motivation for the study.

Beside the impact and causal analyses of the relationship between environmental pollution and economic growth following the EKC model, forecasting and predictability of CO_2 emissions have also gained so much prominence in the literature. Extensive studies have been devoted to searching for appropriate models to provide accurate and reliable forecasts estimates for emissions in order to aid the formulation and implementation of appropriate policies towards mitigating its menace. Despite the prominence of its use by studies on environment-growth impact analyses, the EKC is sparsely used in forecasting and predictability models on emissions (see Auffhammer et al. (2004), Aldy (2006), Auffhammer and Carson (2008), Halicioglu (2009), Jaunky (2011), Pao and Tsai (2011), Pao et al. (2012) and Pérez-Suárez and López-Menéndez (2015)). Our approach in this study is to apply the EKC model to forecast CO_2 emissions. We extend the studies on emissions forecasting, particularly the time series models to account for impact of economic activities on CO_2 emissions. In addition, our approach, which is discussed in detail in the next section, carefully accounts for some of the prominent features of the considered series and predictors, which are found to enhance the forecast performance of the predictive model. Specifically, we account for time varying feature of the parameters of EKC model using the rolling window approach and we also reflect persistence and endogeneity effects, which may affect the outcome of the forecast.

3.0 Methodology

3.1 The Model

As previously explained, we favour the EKC as the underlying framework for forecasting emissions over the time series models. The traditional EKC model is given as:

$$c_t = \alpha_0 + \alpha_1 y_t + \alpha_2 y_t^2 + \varepsilon_t \tag{1}$$

where c_t is a measure of emissions and y_t is a measure of real economic activity. Theoretically, the inverted U-shaped EKC hypothesis is confirmed if $\alpha_1 > 0$ and $\alpha_2 < 0$. We consider equation (1) as the baseline model involving the Ordinary Least Squares (OLS) estimator; thus, ignoring the underlying statistical properties of the income variables. This may bias the regression estimates if these effects truly exist and are ignored in the estimation process (see Lewellen, 2004; Westerlund and Narayan, 2012, 2015). Thereafter, we consider an expanded model that accounts for the three prominent effects namely persistence, endogeneity and conditional heteroscedasticity effects often exhibited by a typical time series variable.

A simple representation of the underlying predictive model of the WN estimator for a single factor was first developed by Lewellen (2004) and can be expressed as:

$$c_t = \alpha + \beta y_{t-1} + \gamma\left(y_t - \rho y_{t-1}\right) + \varepsilon_t \tag{2}$$

where c_t and y_t are as previously defined. The equation (2) is a re-parameterization of both persistence and endogeneity effects.[3] Solving for y_{t-1} above gives a bias-adjusted OLS estimator of β which is described as the Lewellen estimator (see also Salisu and Isah, 2018; Salisu et al., 2018).[4]

$$\beta_{adj} = \beta - \gamma\left(\rho - 1\right) \tag{3}$$

The predictability of income in the EKC-based emission model is evaluated under the null hypothesis that $\beta_{adj} = 0$. Thus, the real economic activity is considered a good predictor of emissions if the null hypothesis is rejected; otherwise, it is not. The additional term in equation (2), i.e., $\gamma\left(y_t - \rho y_{t-1}\right)$ is incorporated to resolve any bias due to the endogeneity and persistence effects, which are respectively captured as γ and ρ.

In addition to the mentioned effects, another important characteristic feature of time series predictors is the conditional heteroscedasticity effect, particularly when dealing with high-frequency series. To deal with this, WN (2012, 2015) propose a Feasible Quasi GLS (FQGLS) estimator and is given as:

$$\beta_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \hat{\tau}_t^2 y_{t-1}^d c_t^d}{\sum_{t=q_m+2}^{T} \hat{\tau}_t^2 \left(c_{t-1}^d\right)^2} \tag{4}$$

where $\hat{\tau}_t = 1/\hat{\sigma}_{\varepsilon,t}$ is used in weighting all the data in the predictive model, $y_t^d = y_t - \sum_{s=2}^{T} y_t/T$ and $c_t^d = c_t - \sum_{s=2}^{T} c_t/T$. In other words, the WN-based estimator

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[3] The equation (2) is the resulting equation from a simple predictive model expressed as $c_t = \mu + \beta c_{t-1} + \upsilon_t$ and based on the underlying assumptions that the persistence and endogeneity effects respectively follow the specifications as $y_t = \vartheta(1-\rho) + \rho y_{t-1} + e_t$ and $\hat{\upsilon}_t = \gamma \hat{e}_t + \varepsilon_t$. The equation (2) is obtained by re-parameterizing the resulting equation after substituting the expressions for the two effects into the simple predictive model. Note that $\alpha = \mu + \gamma\vartheta(1-\rho)$.

[4] See the LW (2004), WN (2012, 2015), Narayan and Gupta (2015), Salisu and Isah (2018) and Salisu et al. (2018) for useful references as regards the underlying derivations for resolving any bias arising from endogeneity and persistence in the predictive model.

involves pre-weighting each of the series in equation (2) with $\hat{\tau}_t = 1/\hat{\sigma}_{\varepsilon,t}$ in order to exploit any information inherent in the conditional heteroscedasticity.

One of the limitations of the WN estimator is that it does not allow for time-varying parameter, although, this is circumvented in this paper by using the rolling window approach of forecasting.[5] To test whether the choice of estimator matters for the EKC-based emission forecast, we consider two estimators namely OLS and WN estimators. In addition, the preferred estimator between the two competing estimators is compared with the univariate time series models - ARIMA and ARFIMA models. A generalized specification for ARIMA (p,d,q) is given below (see also Salisu and Isah, 2018)

$$\left(1-\sum_{i=1}^{p}\rho_i L^i\right)(1-L)^d c_t = \mu + \left(1-\sum_{i=1}^{q}\phi_i L^i\right)\varepsilon_t \tag{7}$$

where μ is the drift parameter, L denotes the lag operator, p and q are the maximum lags for c_t and ε_t, respectively, while d is the order of integration of c_t is differenced to achieve stationarity. For ARFIMA model, the $(1-L)^d$ is described as the fractional differencing operator computed as:

$$(1-L)^d = \sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)} \tag{8}$$

where $\Gamma(\cdot)$ denotes the generalized factorial function. The parameter d is allowed to assume any real value. Restricting d to integer values gives rise to the standard ARIMA model. The emission series c_t is both stationary and invertible if $\left(1-\sum_{i=1}^{p}\rho_i L^i\right)$ and $\left(1-\sum_{i=1}^{q}\phi_i L^i\right)$ lie outside the unit circle and $|d| < 0.5$. The process is non-stationary for $d \geq 0.5$, as it possesses infinite variance (Salisu and Isah, 2018).

3.2 Estimation and forecast procedure

We begin our analyses by pre-testing each of the variables for endogeneity, persistence and conditional heteroscedasticity effects. This is necessary to justify our choice of estimator for the EKC-based emission forecast model. Thereafter, the two competing estimators namely

[5] An alternative approach which involves the expanding window approach usually described as the recursive approach is proposed by Devpura et al. (2018).

OLS and WN estimators are used to establish the predictability of the real economic activity in the forecast of emissions. The comparative forecast performance of the two estimators is also evaluated. Subsequently, the preferred forecast estimator for the EKC model is compared with the time series models. We employ both the Root Mean Square Error (RMSE)) and the Mean Absolute Error (MAE) as forecast measures. In addition, the Campbell and Thompson [C-T] (2008) test is also used as a complementary measure of forecast performance for RMSE and MAE. The C-T test is also favoured here as it facilitates the comparison of two forecast models/estimators being a pairwise forecast measure. The C-T test is computed as $1-\left(M\widehat{S}E_1 / M\widehat{S}E_0\right)$, where $M\widehat{S}E_1$ and $M\widehat{S}E_0$ are the mean square error (MSE) of the prediction from the unrestricted and restricted models, respectively. A positive C-T statistic implies that the unrestricted model outperforms the restricted model, while the reverse is the case for a negative statistic. We also consider the Diebold and Mariano (D-M) test in order to test whether the C-T statistic is statistically different from zero or not. In other words, the D-M test is used to test for the equality of forecast accuracy of two forecasts and is computed as:

$$\text{DM stat} = \frac{\bar{d}}{\sqrt{\frac{1}{T}V\left(d\right)}} \sim N\left(0,1\right) \tag{9}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T}\left[f\left(\varepsilon_{it}\right) - f\left(\varepsilon_{jt}\right)\right]$ is the sample mean loss differential and $V\left(d\right)$ is the unconditional variance of d. The $\left\{\varepsilon_{it}\right\}_{t=1}^{T}$ and $\left\{\varepsilon_{jt}\right\}_{t=1}^{T}$ are the forecast errors associated with the two forecasts say $\left\{\hat{z}_{it}\right\}_{t=1}^{T}$ and $\left\{\hat{z}_{jt}\right\}_{t=1}^{T}$ respectively. The $f\left(\varepsilon_{it}\right)$ and $f\left(\varepsilon_{jt}\right)$ are the loss functions associated with these two forecasts while $d_t \equiv f\left(\varepsilon_{it}\right) - f\left(\varepsilon_{jt}\right)$ is the loss differential. The null hypothesis of equal forecast accuracy for two forecasts is that $E\left[d_t\right] = 0$. There is relative equality between the two forecasts if the null hypothesis of the D-M test is not rejected; otherwise, it is not (Salisu and Isah, 2018).

For robustness purpose, we consider multiple sample structures, using 50% and 75% of total observations as baseline and three forecast horizons for each of the baseline. As previously mentioned, the rolling window approach is adopted, as against the fixed parameter approach, in order to capture any underlying time-varying property of the coefficients of the EKC.

4.0 Data Description and Preliminary Analyses

In this study, we employ quarterly CO_2 emissions and output for the US over the periods 1973 and 2017. The energy data (in million metric tons) was obtained from US Energy Information Administration (EIA) database, while the output data (in Billion USD) was extracted from FRED database at the Federal Reserve Bank of St Louis: https://fred.stlouisfed.org/, respectively. The total CO_2 emission comprises CO_2 emissions from different sources, which include aviation gasoline, coal, distillate fuel oil, hydrocarbon gasoline, jet fuel, kerosene, lubricants, motor gasoline, natural gas, other petroleum, petroleum coke and residential fuels. Owing to the highly mechanized and industrial characteristic of the US economy, besides the total CO_2 emissions, we also consider CO_2 emissions generated from the industrial sector. For robustness purposes, the actual data series, both output and emission data, were converted into their per capita values (by dividing the actual values by US population) and incorporating such in the estimation. For further robustness, we use the industrial production index as an alternative measure of economic output.

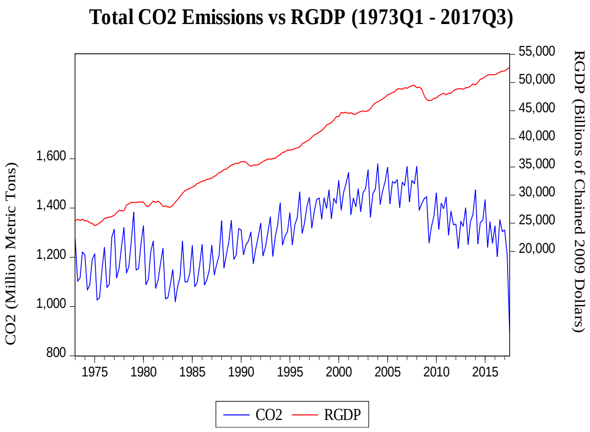
Table 2 gives us an overview of the statistical characteristics (mean, standard deviation skewness, kurtosis and Jarque-Bera statistics) of the data series in actual terms and also in per capita terms. On the average, the total CO_2 emissions is estimated at approximately 1,298.37million metric tons, with about 414.39million metric tons (about a third of the total) emanating from the industrial sector. US output, which averaged 38,822.89billion USD for the period considered seemed to be widely spread away from its central tendency measure, as shown by the large standard deviation value (8,761.89billion USD). We observed CO^2 emissions (total and industrial) and output in actual terms to be negatively skewed, with CO_2 emissions from the industrial sector being leptokurtic, while total CO_2 emissions and output were both platykurtic. The JB statistics reveals total CO_2 emission (in actual terms) to be normally distributed, while the industrial sector CO_2 emissions and RGDP are not normally distributed. On the other hand, in per capita terms, total CO_2 emission and RGDP are not normally distributed.

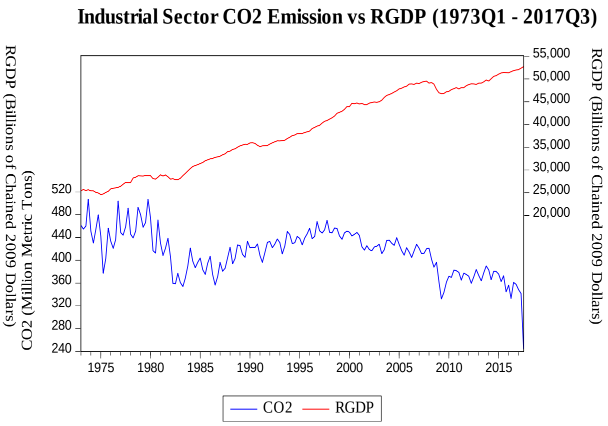
Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	No. of Obs.
			Actual			
Industrial Sector	414.3939	38.6953	-0.4667	4.1795	16.8728***	179
Total Emissions	1,298.3790	140.1413	-0.1620	2.3292	4.1392	179
RGDP	38,822.8900	8,761.8880	-0.0769	1.5818	15.1774***	179
			Per capita			
Industrial Sector	0.0016	0.0003	0.2017	2.7992	1.5148	179
Total Emissions	0.0049	0.0005	-0.5188	4.5499	25.9457***	179
RGDP	10,679.5200	3,699.4720	0.1175	1.6043	14.9404***	179

Note: ***, ** and * represent statistical significance of the Jarque-Bera test statistic at 1%, 5% and 10%, respectively.

We next proceed to graphically examine the relationship between CO_2 emissions (total and industrial sector) and output (RGDP) for the US economy. This is to enable us trace periods of co-movements between the compared variables. Figure 1 shows a mixture of positive and negative relationships between CO_2 emissions and RGDP in support of the Environmental Kuznets Curve (EKC) hypothesis (Grossman and Krueger, 1991; Grossman and Krueger, 1995; Coondoo and Dinda, 2002; Haisheng *et al.*, 2005; Plassmann and Khanna, 2006; Ang, 2007; Ghosh, 2008; Halicioglu, 2009; Apergis and Payne, 2010; Fodha and Zaghdou, 2010; Ozturk and Acaravci, 2010; Iwata et al., 2011; Nasir and Rehman, 2011; Alam et al., 2012; Franklin and Ruth, 2012; Saboori et al., 2012; Narayan and Narayan, 2010; Ahmed and Long, 2013; Baek and Kim, 2013; Kohler, 2013 and Shahbaz *et al*., 2014; among others). The CO_2 emission from the industrial sector follows a similar pattern as total CO_2 emission, a confirmation of the substitutability of the former for the latter with respect to the US economy.





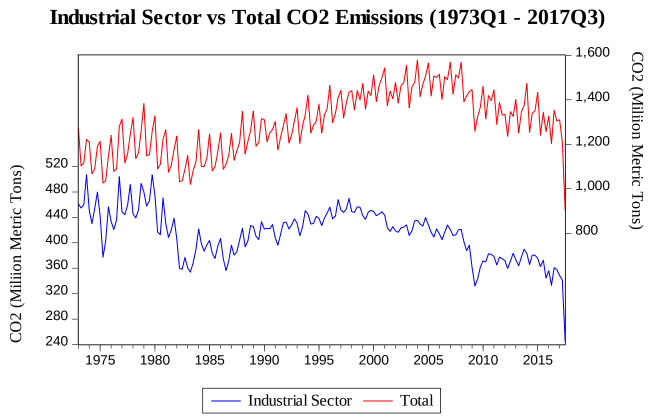


Figure 1: Trends in (Industrial Sector and Total) CO_2 emissions and output

Table 4 shows the result of the conditional heteroscedasticity (using Engle's ARCH LM test) and serial correlation (using Ljung-Box Q- and Q^2-Statistics tests) for the series, both in actual and in per capita terms, under three different lag specifications (5, 10 and 20) to ensure robustness. The tests are informed on the grounds of the basic requirement for the use of the WN estimator. All the series show varying evidence of conditional heteroscedasticity and serial correlations at the different specified lag orders for both actual and per capita series. We further subject the predictor variables to endogeneity and persistence test (see results in Table 5). The predictors, both in actual terms and in per capita terms, are all exogenous and show evidence of high persistence.

Table 4: Conditional Heteroscedasticity and Serial Correlation Tests

	Heteroscedasticity Test			Serial Correlation Test					
	$ARCH(5)$	$ARCH(10)$	$ARCH(20)$	$Q(5)$	$Q(10)$	$Q(20)$	$Q^2(5)$	$Q^2(10)$	$Q^2(20)$
				Actual					
INDS	1.5788	1.3487	0.6550	59.24^{***}	146.45^{***}	251.27^{***}	1.48	2.69	3.58
TOT	23.2886^{***}	10.7928^{***}	5.2399^{***}	132.07^{***}	251.31^{***}	575.68^{***}	46.97^{***}	82.88^{***}	166.86^{***}
RGDP	2.0205^{*}	1.8532^{*}	1.8659^{**}	36.69^{***}	42.58^{***}	73.40^{***}	12.17^{**}	26.38^{***}	43.93^{***}
$RGDP^2$	2.0018^{*}	1.7430^{*}	1.6910^{**}	37.22^{***}	42.84^{***}	72.34^{***}	11.64^{**}	23.35^{**}	38.08^{***}
				Per Capita					
INDS	2.0489^{*}	1.6178	0.6226	66.95^{***}	167.78^{***}	282.62^{***}	2.43	4.18	5.83
TOT	6.3403^{***}	4.4660^{***}	2.7758^{***}	123.10^{***}	233.90^{***}	531.94^{***}	7.51	14.57	28.70^{*}
RGDP	2.0441^{*}	1.7772^{*}	1.8507^{**}	36.87^{***}	42.65^{***}	69.71^{***}	12.23^{**}	25.68^{***}	43.28^{***}
$RGDP^2$	2.0429^{*}	1.6220	1.5589^{*}	37.95^{***}	43.26^{***}	67.80^{***}	11.51^{**}	20.93^{**}	33.80^{**}

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. The ARCH-LM test (Engle, 1982) tests for conditional heteroscedasticity under the null hypothesis of no ARCH effect (that is, there is no presence of conditional heteroscedasticity). The F-statistic is reported for the ARCH-LM test. The serial correlation test conducted involves both the Q-statistics and the Q^2-statistics of Ljung-Box, with the underlying null hypothesis of no serial correlation. For robustness, both tests are conducted at three different lag orders (5, 10, and 20).

Table 5: Testing for persistence and endogeneity in the predictors

	PERSISTENCE		ENDOGENEITY	
	Industrial Sector	**Total Emissions**	**Industrial Sector**	**Total Emissions**
		Actual		
RGDP	0.9971^{***}	0.9971^{***}	-0.0033	-0.5941
$RGDP^2$	0.9974^{***}	0.9974^{***}	0.0009	-0.0284
		Per Capita		
RGDP	0.9977^{***}	0.9977^{***}	0.2805	-0.5008
$RGDP^2$	0.9983^{***}	0.9983^{***}	0.0159	-0.0288

Note: This table reports the endogeneity and persistence test results. The statistical significance of the tests at 1%, 5% and 10% are denoted by ***, ** and *, respectively. On the endogeneity test, the underlying null hypothesis is that the predictor is exogenously determined. The test for persistence is conducted by regressing a first order autoregressive process for the predictor, using OLS estimator. The coefficient of the first order autocorrelation term captures the persistence effect and is reported for each predictor. The underlying null is that there is presence of persistence effect, with statistically significant values that are close to one indicating a higher the degree of persistence.

5.0 Discussion of Results

As earlier mentioned, we set out to evaluate the predictability of the US CO_2 emissions using the EKC model as well as to demonstrate how the forecasting accuracy of the EKC can be enhanced to produce better forecast results than the time series models, which have been validated as better forecasting tools for emissions. Our preferred model, the WN estimator, addresses the inherent statistical characteristics of the series, in comparison with the OLS model and time series models that do not. The discussion of results is structured as follows. We begin by evaluating the predictability of output for total and industrial sector CO_2 emissions of the US using the WN estimator for both the actual series and their per capita values for robustness. This is to ascertain the signs and statistical significance of output and its squared term in line the EKC original propositions.

We next evaluate the individual forecast performance of competing models using the mean absolute error (MAE) and the root mean square error (RMSE). Based on the MAE and RMSE, forecast performance preference is made based on the closeness of their statistic to zero. We further evaluate the forecast performance of the competing models using the Campbell Thompson (C-T) and Diebold and Mariano (D-M) tests, with the preferred WN estimator as our benchmark estimator. The forecast evaluation is carried out for different sample structures (baseline at 50% and 75% of the full sample) and the specified periods ahead forecast horizons (6, 12 and 24 quarters). Lastly, for robustness checks, we replaced the output measures used for the main estimation (*RGDP* and *RGDP*^{2}) with index of industrial of industrial production (*IPI*) and its squared value. We present and discussed the robustness results in section 5.4.

5.1 CO_2 Emission Predictability of the EKC Model

Testing the CO_2 emission predictability of the EKC model using the WN estimator is premised not only on its encompassing characteristics, which allows for the adjustment of the series for the inherent statistical characteristics, but also on the fact that it is intended to be the reference estimator in this study. This is also compared with the OLS estimator, which is a baseline for every regression analysis. Table 6 shows that both *RGDP* and *RGDP*^{2} contribute significantly to the model performance regardless of the choice of CO_2 emission used in both actual and per capita terms. We find the signs of the coefficients conforming to the apriori expectation of the EKC model, which is the inverted U-shaped relationship between economic growth and CO_2 emission, using both OLS and WN estimators. This not only reveals the importance of output in the prediction of CO_2 emission, but also confirms the EKC hypothesis for the US economy (see Grossman and Krueger, 1995 and Apergis et al. 2017 among others).

Table 6: CO_2 Emission Predictability of the EKC Model

	Actual				Per Capita			
	Industrial Sector		Total Emission		Industrial Sector		Total Emission	
	RGDP	*RGDP*^{2}	*RGDP*	*RGDP*^{2}	*RGDP*	*RGDP*^{2}	*RGDP*	*RGDP*^{2}
WN	10.8388*** (3.2081)	-0.5246*** (0.1527)	8.3625*** (2.9156)	-0.3823*** (0.1387)	5.0146*** (1.1936)	-0.3003*** (0.0650)	5.1649*** (1.1113)	-0.2899*** (0.0605)
OLS	10.3096*** (3.1424)	-0.4987*** (0.1495)	6.9003** (2.8773)	-0.3130** (0.1369)	4.9486*** (1.1613)	-0.2957*** (0.0633)	4.5524*** (1.0866)	-0.2567*** (0.0592)

Note: The statistical significance of the tests at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The values in each cell represent the coefficients of the corresponding predictors, with their standard error placed within parentheses.

5.2 Baseline Forecast Evaluation

Here, we examine the baseline (at 50% and 75%) forecast performance of the competing theoretic model estimator (WN), a baseline regression model estimator (OLS) and selected time series models (ARIMA and ARFIMA) in a view to determine the role of the choice of estimator in the prediction of the CO_2 emissions. On the RMSE and MAE forecast accuracy measures, preference of an estimator is based on its closeness to zero in comparison with other competing estimators. Tables 7a and 7b shows the results for total and industrial sector CO_2 emission using 50% and 75% of the full sample, with CO_2 emissions and output in actual and per capita terms. Comparing the forecast accuracy of these competing models, we observe a pattern of out-performance, in favour of the WN estimator, across the two CO_2 emission proxies used in both actual and per capita terms. While the WN estimator seem to out-perform all the other competing models, we find ARFIMA to be the least performed.

In a pair-wisely comparative analysis, we further subject the models to the Campbell-Thompson (C-T) test (see results in Table 8), and the Diebold and Mariano (D-M) tests (see results in Table 9). Setting the WN estimator as our reference, we observe an out-performance in favour of our reference estimator as indicated by the positive Campbell-Thompson (C-T) test values and the significantly negative Diebold and Mariano (D-M) test values. The performances of the WN and OLS estimators were relatively similar, having infinitesimal difference, especially, when 50% of the full sample was used (see Tables 8 & 9). More generally, WN estimator out-performed the OLS estimator as shown by the positive C-T values and significantly negative D-M values. The WN estimator consistently out-performed the time series models when both total and industrial sector CO_2 emissions and output in actual terms were used in the baseline forecast performance. WE also find a similar feat using CO_2 emissions and output data in per capita terms, except for the case of the ARIMA model with CO_2 emissions from industrial sector. Although, the ARIMA model seemed to out-perform WN estimator relatively, this out-performance was not significant (see D-M test values in Table 9). Overall, the performance of the WN estimator, which take cognisance of the inherent statistical characteristics of the series, is preferred over all other competing models regardless of the baseline sample considered. This, therefore suggests that the choice of estimator do matter in environmentally related studies and is not sensitive to baseline sample.

Table 7a: Forecast Accuracy Result using RMSE

	50%	ALT_1a	ALT_1b	ALT_1c	75%	ALT_2a	ALT_2b	ALT_2c
Panel A: Industrial Sector Emission								
				Actual				
ARIMA	0.0975	0.1080	0.1222	0.1434	0.1642	0.1703	0.1722	0.1739
ARFIMA	0.1046	0.1153	0.1292	0.1491	0.1657	0.1621	0.1587	0.1525
OLS	0.0870	0.0851	0.0856	0.0863	0.0831	0.0828	0.0831	0.0820
WN	0.0867	0.0847	0.0849	0.0853	0.0818	0.0816	0.0819	0.0810
				Per Capita				
ARIMA	0.0897	0.0886	0.0905	0.0939	0.0984	0.1021	0.1031	0.1048
ARFIMA	0.1430	0.1401	0.1365	0.1310	0.1281	0.1252	0.1226	0.1178
OLS	0.0931	0.0906	0.0903	0.0909	0.0878	0.0878	0.0881	0.0870
WN	0.0925	0.0900	0.0894	0.0894	0.0860	0.0861	0.0865	0.0856
Panel B: Total Emission								
				Actual				
ARIMA	0.0733	0.0734	0.0758	0.0829	0.0934	0.0967	0.0974	0.0953
ARFIMA	3.4222	3.3126	3.2146	3.1200	3.3727	3.2985	3.2291	3.1024
OLS	0.0741	0.0728	0.0720	0.0716	0.0717	0.0721	0.0719	0.0705
WN	0.0717	0.0704	0.0697	0.0693	0.0699	0.0702	0.0698	0.0684
				Per Capita				
ARIMA	0.0817	0.0873	0.0980	0.1254	0.1877	0.2121	0.2337	0.2824
ARFIMA	0.0849	0.0915	0.1038	0.1361	0.2156	0.2108	0.2064	0.1983
OLS	0.0802	0.0785	0.0772	0.0769	0.0780	0.0791	0.0789	0.0774
WN	0.0790	0.0773	0.0760	0.0758	0.0771	0.0782	0.0779	0.0763

Note: ALT_1a, ALT_1b and ALT_1c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 50% sample, while ALT_2a, ALT_2b and ALT_2c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 75% sample.

Table 7b: Forecast Accuracy Result using MAE

Panel A: Industrial Sector Emission								
	50%	**ALT_1a**	**ALT_1b**	**ALT_1c**	**75%**	**ALT_2a**	**ALT_2b**	**ALT_2c**
				Actual				
ARIMA	0.0797	0.0878	0.0980	0.1154	0.136	0.1419	0.1443	0.1478
ARFIMA	0.0850	0.0934	0.1037	0.1207	0.1387	0.1326	0.1271	0.1173
OLS	0.0688	0.0673	0.0686	0.0711	0.0691	0.0694	0.0692	0.0685
WN	0.0687	0.0670	0.0681	0.0702	0.0679	0.0683	0.0685	0.0679
				Per Capita				
ARIMA	0.0684	0.0684	0.0712	0.0762	0.0826	0.0861	0.0871	0.0894
ARFIMA	0.1222	0.1200	0.1159	0.1110	0.1107	0.1059	0.1015	0.0937
OLS	0.0727	0.0702	0.0710	0.0735	0.0721	0.0727	0.0726	0.072
WN	0.0724	0.0697	0.0701	0.0720	0.0702	0.0710	0.0714	0.0709
Panel B: Total Emission								
				Actual				
ARIMA	0.0614	0.0613	0.0637	0.0699	0.0795	0.0825	0.0833	0.0811
ARFIMA	3.1652	2.9888	2.8428	2.7644	3.0289	2.8972	2.7765	2.5629
OLS	0.0615	0.0600	0.0596	0.0593	0.0596	0.0602	0.0599	0.0586
WN	0.0593	0.0578	0.0574	0.0575	0.058	0.0586	0.0577	0.0562
				Per Capita				
ARIMA	0.0686	0.073	0.0806	0.0992	0.1415	0.1575	0.1727	0.2067
ARFIMA	0.0709	0.0761	0.0846	0.1059	0.1578	0.1509	0.1446	0.1335
OLS	0.0656	0.0637	0.0627	0.0629	0.0644	0.0658	0.0655	0.064
WN	0.0652	0.0632	0.0623	0.0626	0.0641	0.0654	0.0647	0.063

Note: ALT_1a, ALT_1b and ALT_1c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 50% sample, while ALT_2a, ALT_2b and ALT_2c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 75% sample.

5.3 Alternative Scenarios Forecast Evaluation

Having evaluated the baseline forecast performance, it is good practice to test for the robustness by evaluating alternative scenarios. The alternative scenarios in this study are constituted by considering three different horizons (6, 12 and 24 quarters) in addition to the given baseline (50% and 75%). This is to ensure that the estimation results are similar regardless of the sample periods considered. Tables 7a and 7b show the RMSE and MAE results, respectively, with respect to the out-of-sample forecast performance of the competing models for the 50% of the full sample using both total and industrial sector CO_2 emissions in actual and in per capita terms. Further confirmations were conducted using the C-T and DM tests, which are presented in Tables 8 and 9, respectively. Results revealed similar performance with respect to all the models considered in the in-sample case. Again, we find that the WN estimator generally out-performed the OLS estimator and the time series models (ARIMA and ARFIMA). This stance is confirmed by the positive C-T test (Table 8) and the significantly negative D-M test values (Table 9). The choice of estimator must definitely be taken into consideration regardless of the sample period and the CO_2 emission proxies considered in actual and per capita terms.

Table 8: Campbell Thompson Results

	50%	ALT_1a	ALT_1b	ALT_1c	75%	ALT_2a	ALT_2b	ALT_2c
Panel A: Industrial Sector Emission								
				Actual				
ARIMA	0.1110	0.2155	0.3051	0.4054	0.5019	0.5208	0.5244	0.5342
ARFIMA	0.1710	0.2650	0.3428	0.4281	0.5066	0.4966	0.4839	0.4687
OLS	0.0038	0.0050	0.0078	0.0123	0.0157	0.0141	0.0140	0.0123
				Per Capita				
ARIMA	-0.0317	-0.0152	0.0128	0.0475	0.1263	0.1565	0.1610	0.1839
ARFIMA	0.3527	0.3577	0.3452	0.3176	0.3285	0.3123	0.2946	0.2737
OLS	0.0061	0.0072	0.0105	0.0162	0.0208	0.0193	0.0186	0.0165
Panel B: Total Emission								
				Actual				
ARIMA	0.0221	0.0404	0.0797	0.1636	0.2513	0.2738	0.2837	0.2830
ARFIMA	0.9790	0.9787	0.9783	0.9778	0.9793	0.9787	0.9784	0.9780
OLS	0.0324	0.0325	0.0316	0.0314	0.0243	0.0254	0.0291	0.0310
				Per Capita				
ARIMA	0.0336	0.1144	0.2247	0.3959	0.589	0.6312	0.6667	0.7296
ARFIMA	0.0700	0.1552	0.2681	0.4433	0.6421	0.6290	0.6227	0.6150
OLS	0.0149	0.0150	0.015	0.0152	0.0104	0.0107	0.0129	0.0141

Note: The figures in each cell represent the Campbell-Thompson statistics comparing the listed forecast models with the benchmark model, Westerlund and Narayan. The associated sign of the presented values suggests the order of performance, with positive values indicating a better performance by the benchmark model. ALT_1a, ALT_1b and ALT_1c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 50% sample, while ALT_2a, ALT_2b and ALT_2c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 75% sample.

Table 9: Diebold and Mariano Test Results

	50%	ALT_1a	ALT_1b	ALT_1c	75%	ALT_2a	ALT_2b	ALT_2c
Panel A: Industrial Sector Emission								
					Actual			
ARIMA	-1.4213	-2.7235***	-3.8474***	-5.6706***	-8.3294***	-9.0419***	-9.4038***	-10.3422***
ARFIMA	-1.9582*	-3.1492***	-4.2005***	-5.9755***	-8.5901***	-9.3183***	-9.5734***	-10.1037***
OLS	-1.4427	-1.3306	-1.1647	-0.8017	-0.3488	0.0099	-0.1299	-0.4943
					Per Capita			
ARIMA	0.1127	-0.1084	-0.5043	-0.8792	-2.6037***	-3.4134***	-3.1744***	-3.3550***
ARFIMA	-7.7799***	-8.1311***	-7.9050***	-7.7253***	-9.4086***	-9.7094***	-9.6244***	-10.7462***
OLS	1.079	0.6970	-0.1965	-1.8217*	-3.5133***	-3.9769***	-3.8351***	-2.9783***
Panel B: Total Emission								
					Actual			
ARIMA	-6.2565***	-6.3533***	-6.0578***	-5.4192***	-4.2784***	-3.9460***	-4.0509***	-4.7570***
ARFIMA	-14.6047***	-13.6044***	-13.0535***	-13.8246***	-15.5141***	-15.5067***	-15.6701***	-16.8466***
OLS	-11.4989***	-11.8391***	-11.7566***	-11.4566***	-10.9268***	-10.7227***	-10.9899***	-12.0529***
					Per Capita			
ARIMA	3.3917***	2.7316***	1.4197	-1.0199	-4.4566***	-5.1321***	-5.5372***	-6.5547***
ARFIMA	3.8274***	3.7701***	3.8652***	4.9408***	6.5589***	7.1126***	6.5562***	6.0583***
OLS	1.5631	1.4839	1.0527	-0.1884	-1.8885*	-2.5374**	-2.7306***	-2.4655**

Note: The Diebold and Mariano (DM) test is a formal test that is used to confirm the significance of the model forecast performance. The statistical significance of the Diebold and Mariano (DM) statistics at 1%, 5% and 10% are represented by ***, ** and *, respectively. ALT_1a, ALT_1b and ALT_1c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 50% sample, while ALT_2a, ALT_2b and ALT_2c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 75% sample.

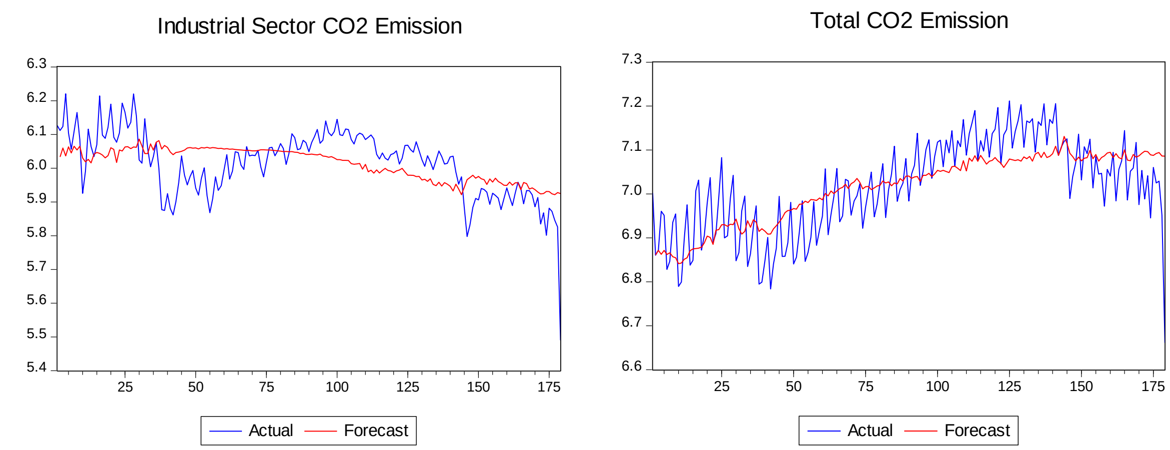


Figure 2: CO_2 Emissions Forecast Performance of the WN estimator

5.4 Robustness Checks

Here, we test whether the estimated results are not sensitive to the choice of output proxy as an additional robustness check to the use of actual and per capita series for both output and CO_2 emissions. As earlier mentioned, given the inherent characteristics of the US economy and evidence in literature on the appropriateness of using the industrial production index (IPI) as an alternative measure of economic output (see UN, 2010) we embark on a similar sequence of estimations (Tables 6 to 9) using IPI as a proxy for output. Using, IPI, we evaluate the EKC model predictability of CO_2 emission (see Table 10 for summary of estimated coefficients). We also evaluate the forecast performance, both the baseline and alternative scenarios, using various forecast accuracy measure - RMSE and MAE (Table 11), C-T test and D-M test (Table 12). The results obtained are very much the same as what was obtained with RGDP as the measure of economic output. These results suggest that the estimates are not sensitive to the choice of output proxy used and further uphold our stance of the preference of the WN estimator over the other competing predictor models – OLS and the time series models (ARIMA and ARFIMA).

Table 10: Carbon Emission Predictability Results (using IPI)

WN				OLS			
Industrial Sector		**Total Emission**		**Industrial Sector**		**Total Emission**	
IPI	*IPI*^{2}	*IPI*	*IPI*^{2}	*IPI*	*IPI*^{2}	*IPI*	*IPI*^{2}
1.9926**	-0.2475**	1.9845**	-0.2011**	1.9942**	-0.2472**	1.7478**	-0.1738*
(0.9644)	(0.1133)	(0.8019)	(0.0942)	(0.9491)	(0.1115)	(0.7763)	(0.0912)

Note: The statistical significance of the tests at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The values in each cell represent the coefficients of the corresponding predictors, with their standard error placed within parentheses.

Table 11: Root Mean Square and Mean Absolute Error using IPI

Panel A: Industrial Sector Emission								
	50%	**ALT_1a**	**ALT_1b**	**ALT_1c**	**75%**	**ALT_2a**	**ALT_2b**	**ALT_2c**
	Root mean Square Error							
ARIMA	0.0974	0.0942	0.0913	0.0862	0.1640	0.1603	0.1570	0.1508
ARFIMA	0.1044	0.1010	0.0979	0.0925	0.1655	0.1619	0.1585	0.1523
OLS	0.0846	0.0819	0.0794	0.0751	0.0832	0.0814	0.0797	0.0766
WN	0.0842	0.0815	0.0790	0.0746	0.0815	0.0797	0.0781	0.0750
	Mean Absolute							
ARIMA	0.0796	0.0745	0.0699	0.0624	0.1358	0.1299	0.1245	0.1149
ARFIMA	0.0849	0.0794	0.0746	0.0665	0.1385	0.1325	0.1270	0.1172
OLS	0.0671	0.0628	0.0591	0.0528	0.0695	0.0665	0.0638	0.0590
WN	0.0662	0.0620	0.0583	0.0521	0.0676	0.0647	0.0620	0.0572
Panel B: Total Emission								
	Root mean Square Error							
ARIMA	0.0724	0.0700	0.0679	0.0641	0.0922	0.0902	0.0883	0.0848
ARFIMA	3.3785	3.2677	3.1671	2.9910	3.3295	3.2563	3.1878	3.0627
OLS	0.0678	0.0656	0.0636	0.0602	0.0648	0.0634	0.0621	0.0597
WN	0.0668	0.0646	0.0627	0.0592	0.0639	0.0625	0.0612	0.0588
	Mean Absolute							
ARIMA	0.0606	0.0567	0.0533	0.0475	0.0785	0.0751	0.0719	0.0664
ARFIMA	3.1248	2.9232	2.7460	2.4491	2.9901	2.8601	2.7400	2.5301
OLS	0.0574	0.0537	0.0505	0.0452	0.0542	0.0519	0.0498	0.0460
WN	0.0558	0.0523	0.0491	0.0439	0.0529	0.0506	0.0485	0.0448

Note: ALT_1a, ALT_1b and ALT_1c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 50% sample, while ALT_2a, ALT_2b and ALT_2c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 75% sample.

Table 12: Campbell-Thompson and Diebold & Mariano Results

Panel A: Industrial Sector Emission

	50%	**ALT_1a**	**ALT_1b**	**ALT_1c**	**75%**	**ALT_2a**	**ALT_2b**	**ALT_2c**
				Campbell Thompson Test				
ARIMA	0.1355	0.1352	0.1349	0.1344	0.5029	0.5028	0.5027	0.5026
ARFIMA	0.1938	0.1935	0.1932	0.1928	0.5076	0.5075	0.5075	0.5073
OLS	0.0045	0.0049	0.0052	0.0057	0.0202	0.0204	0.0205	0.0208
				Diebold & Mariano Test				
ARIMA	-1.7666*	-3.0272***	-4.0939***	-5.8819***	-8.5068***	-9.2044***	-9.5365***	-10.2649***
ARFIMA	-2.3980**	-3.5433***	-4.5315***	-6.2709***	-8.8901***	-9.6206***	-9.8550***	-10.1450***
OLS	-0.5346	-0.828	-1.9115*	-2.0154**	-2.0308**	-2.1736**	-2.0558**	-0.8623

Panel B: Total Emission

	50%	**ALT_1a**	**ALT_1b**	**ALT_1c**	**75%**	**ALT_2a**	**ALT_2b**	**ALT_2c**
				Campbell Thompson Test				
ARIMA	0.0775	0.0771	0.0768	0.0763	0.3071	0.307	0.3069	0.3067
ARFIMA	0.9802	0.9802	0.9802	0.9802	0.9808	0.9808	0.9808	0.9808
OLS	0.0148	0.0152	0.0155	0.016	0.0144	0.0145	0.0147	0.0149
				Diebold & Mariano Test				
ARIMA	-2.2658**	-2.6946***	-3.6435***	-5.1298***	-7.3635***	-8.0093***	-8.2971***	-8.1299***
ARFIMA	-15.0200***	-13.9790***	-13.2610***	-13.5570***	-15.8970***	-16.0550***	-16.2700***	-17.4500***
OLS	-0.0673	-0.0844	-0.2281	-0.2321	-0.4424	-0.4333	-0.0841	0.0141

Note: The figures in each cell represent the Campbell-Thompson statistics comparing the listed forecast models with the benchmark model, Westerlund and Narayan. The associated sign of the presented values suggests the order of performance, with positive values indicating a better performance by the benchmark model. The Diebold and Mariano (DM) test is a formal test that is used to confirm the significance of the model forecast performance. The statistical significance of the Diebold and Mariano (DM) statistics at 1%, 5% and 10% are represented by ***, ** and *, respectively. ALT_1a, ALT_1b and ALT_1c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 50% sample, while ALT_2a, ALT_2b and ALT_2c represent alternative forecast horizons at 6, 12 and 24 quarters, respectively based on 75% sample.

6.0 Conclusion

This study provides evidence-based result on estimation methods that would improve the forecast accuracy of the Environmental Kuznets Curve using quarterly CO_2 emissions and output proxies for the US economy. We provide answers to two key questions – (i) does the choice of estimator matter in the predictability of the EKC for the US economy? and (ii) how sensitive are estimated result to different proxies (CO_2 emission and output) and sample structure? First, we confirmed that the choice of estimator does matter in the predictability of the EKC for the US economy by evaluating the CO_2 emission predictability results for WN and OLS. Our findings support the EKC hypothesis - inverted U-shaped relationship between CO_2 emissions and output. On the forecast evaluation, we considered two different sample structures (50% and 75%), data measures (actual and per capita), CO_2 emissions (industrial sector and total) and output (*RGDP*). Although, we found infinitesimal differences between the WN and OLS estimators at 50% sample, WN estimator generally out-perform OLS and the univariate time series models (ARIMA and ARFIMA) considered. On the robustness of estimates, we subject our models to further sensitivity checks using a different output proxy (*IPI*) in addition to previous robustness checks. Our results were found to be robust and not sensitive to the structure of the estimation procedure.

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Appendices

Table 3_a: Unit Root Test Results

	INDS		TOT		RGDP	
	ADF	**PP**	**ADF**	**PP**	**ADF**	**PP**
LEVEL						
Actual						
None	-1.1560	-1.2219	-0.4214	-0.6806	4.1791	4.6606
Constant	-0.2665	-1.3531	-1.0660	-5.7897***	-0.8743	-0.9628
Constant & Trend	-1.1270	-2.7969	0.6180	-8.2118***	-1.4668	-1.4988
Per Capita						
None	1.9516	2.1026	1.5442	1.5297	5.7404	7.2729
Constant	0.6704	0.7210	1.4934	-5.8139***	-0.9914	-1.0670
Constant & Trend	-1.4433	-3.2655*	0.3101	-9.0276***	-1.0919	-1.1246
FIRST DIFFERENCE						
Actual						
None	-5.8877***	-12.0396***	-4.2099***	-24.5922***	-5.2257***	-8.3983***
Constant	-6.0628***	-12.0836***	-4.1674***	-24.4425***	-9.1247***	-9.3690***
Constant & Trend	-6.1431***	-12.1363***	-4.3771***	-25.2035***	-9.1292***	-9.3625***
Per Capita						
None	-5.4553***	-11.8838***	-4.0160***	-24.0995***	-4.2047***	-6.9612***
Constant	-6.1469***	-12.1047***	-4.2589***	-24.7408***	-9.1044***	-9.3588***
Constant & Trend	-6.1983***	-12.1440***	-4.4272***	-25.4020***	-9.1373***	-9.3730***

Note: The ***, ** and * represent statistical significance of the unit root test statistic at 1%, 5% and 10%, respectively.