Forecasting CO2 emissions using ARIMA models in Brazil, China, EU, India and US

Time Series Analysis Term Paper

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Contents

Motivation

Increasing evidence has shown that human emissions of carbon dioxide and other greenhouse gases are a primary driver of climate change (Stocker et al. [2014]). This makes worldwide emissions one of the world's most pressing challenges and has provoked various international agreement, like the Paris Agreement on emission reduction and other climate goals. Three of the largest current emitting regions are China, the US and the EU.

Introduction

The main topic of this term paper is to analyze and model the trends of CO2 emissions in some of the countries of the European Union, the United States of America and China (and perhaps comparing them with emerging economics such as Brazil and India). Current actions to mitigate the climate effects of such steep rise of CO2 emissions over the last 50-60 years are not enough to reach the goals set in the Paris Agreement by 2030. Such is the slow response from the governing institutions and international organizations that the current trends indicate that the temperature increases (and all the consequences behind it) will be irreversible in the future. This paper will analyze the trends of CO2 emissions of the above-mentioned countries and will design a fitting Auto Regressive Integrated Moving Average (ARIMA) model. Next, we will run diagnostics and perform the necessary tests to assure that the model accounts for stationarity and possibly seasonality. Lastly, a forecast for the next periods based on the model will be presented.

Literature review

There have been several studies that apply ARIMA models and similar statistical and econometric techniques to forecast carbon dioxide emissions for different regions, countries and time periods.

Fatima et al. [2019] used Simple Exponential Smoothing (SES) and ARIMA models to forecast CO2 emissions for several Asian countries, with China and India among them. For China they fit an (1,2,0) ARIMA model and for India an (0,2,1) ARIMA model.

Nyoni and Mutongi [2019] modeled an ARIMA model for CO2 emissions in China for the period 1960-2014, they found that an ARIMA(1,2,1) model is the most suitable model to forecast total annual CO2 emissions for China.

A study on carbon dioxide emissions between 1972 and 2015 in Bangladesh was conducted by Rahman and Hasan [2017]. According to their results, the best fitting ARIMA model was of order (0,2,1).

One of the justifications some of these authors mention when choosing to forecast using ARIMA models was that no other data is necessary, the forecasting can be done using only historical values of the data, with no other variables involved.

The model and data

In this section, we go over the data, its characteristics, sources and reliability. Moreover, we introduce the ARIMA (Auto Regressive Integrated Moving Average) model in a formal way, next, we run the model on our data to then set up all the insights to analyze in the following section.

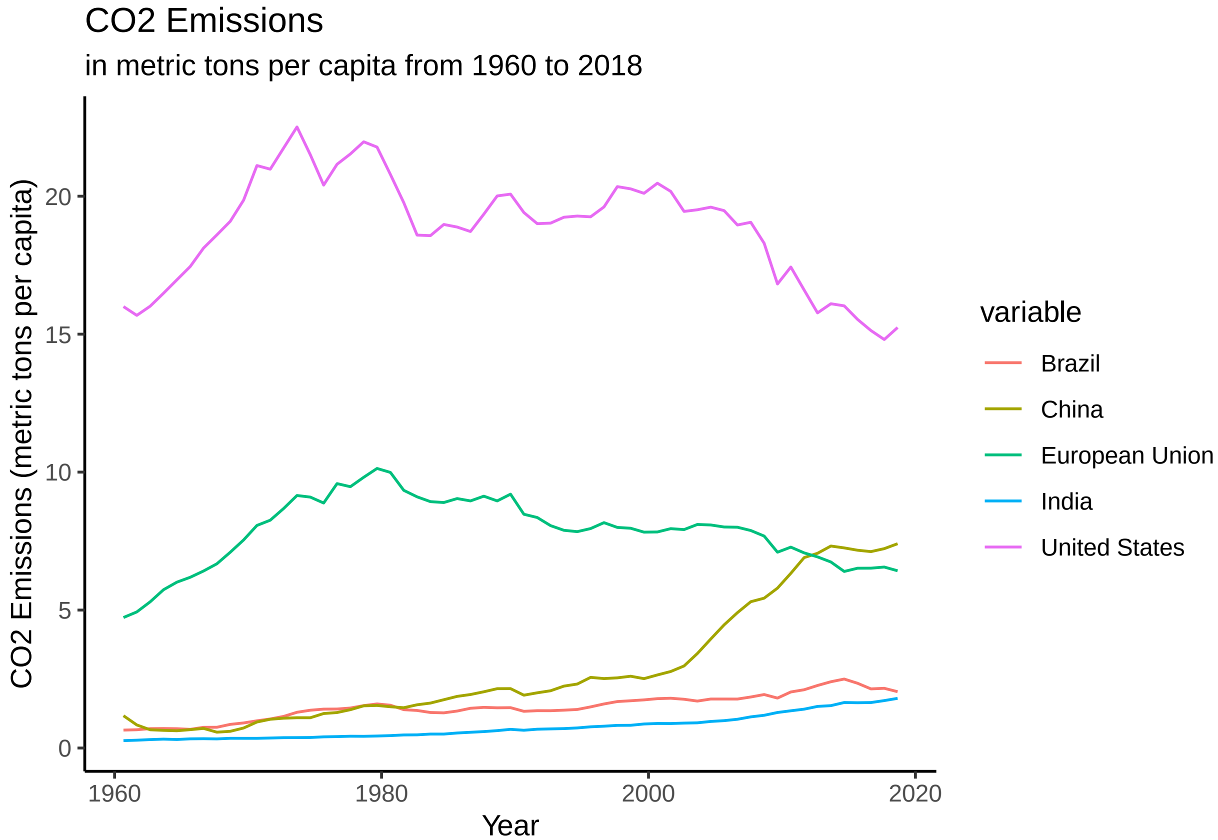
All data is taken from the World Bank's Database. This database has proven to be reliable for industrialized countries, not so much for developing countries, since data from these countries might not be recollected or administered correctly by the corresponding authorities.

As stated in the Introduction, our interest here is to analyze the trends of the 3 biggest emitters of CO2 in the world: the United States of America, the European Union and China . Additionally, we compare those trends and forecast, with trends and forecast of emerging economies such as Brazil and India, as those countries display worrying trends on CO2 emissions that are product of contamination and deforestation due to their growing industries.

The measure we use for our analysis is C02 emissions per capita, because although all country groups are the among the biggest in terms of surface, the population density is different and thus “spreading” the CO2 emissions by population gives us more sensible data and accounted for the different sizes of population.

Table 1: Summary statistics for all countries

	Brazil	China	European Union	India	United States
	Min. :0.6499	Min. :0.5742	Min. : 4.729	Min. :0.2676	Min. :14.81
	1st Qu.:1.2913	1st Qu.:1.2103	1st Qu.: 7.000	1st Qu.:0.3929	1st Qu.:17.44
	Median :1.4577	Median :2.0384	Median : 7.966	Median :0.6441	Median :19.24
	Mean :1.4862	Mean :2.8182	Mean : 7.845	Mean :0.7551	Mean :18.86
	3rd Qu.:1.7758	3rd Qu.:3.6886	3rd Qu.: 8.914	3rd Qu.:0.9382	3rd Qu.:20.14
	Max. :2.4994	Max. :7.4052	Max. :10.133	Max. :1.7998	Max. :22.51



As seen above, CO2 emissions of the countries of interest are showing different trends and magnitudes.[1]

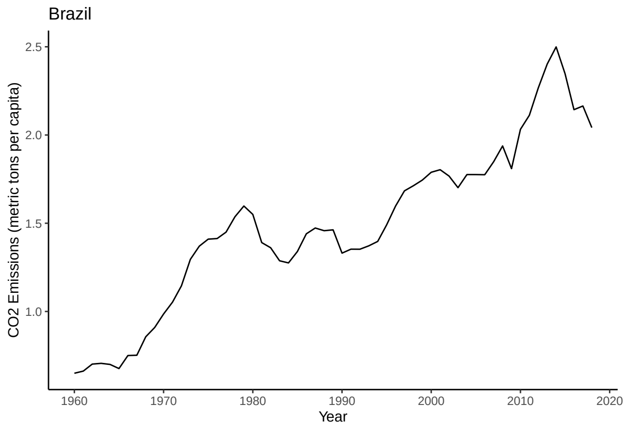
Even though the European Union and the United States show some decline in emissions after the 1980s, the level of emissions are significantly higher than emerging countries like Brazil or India. The worrying part is that China's carbon dioxide emissions surpassed the ones from the European Union in the last 10 years, the steep rise since the early 2000s matches Chinas rising role as a main actor in the global economy.

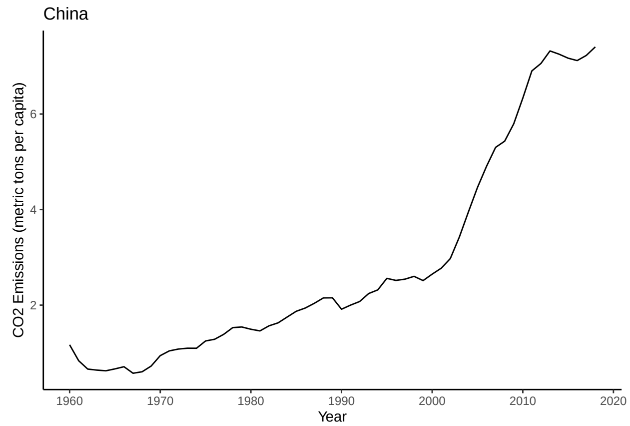
Below are the summary statistics for all countries and their respective time series plots (the time period of the data recollected is from 1960 to 2018 for all countries)

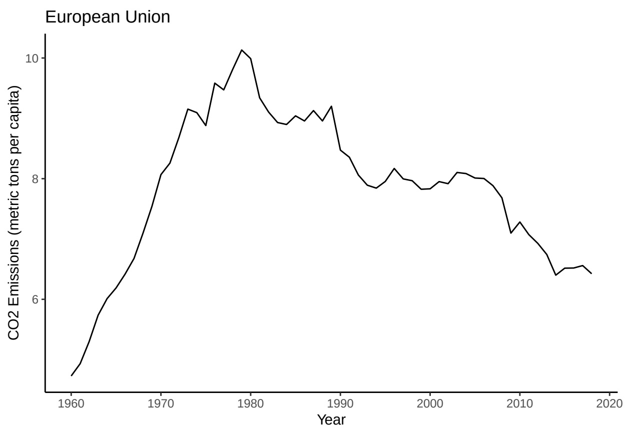
[1] For a more detailed view of each countries' time series see next section of the paper

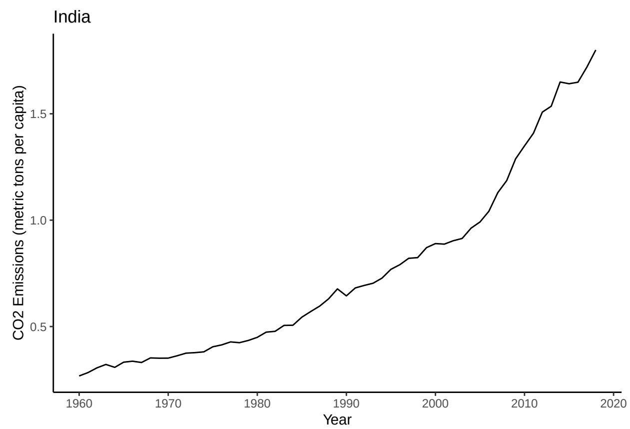
Individual Time series plots

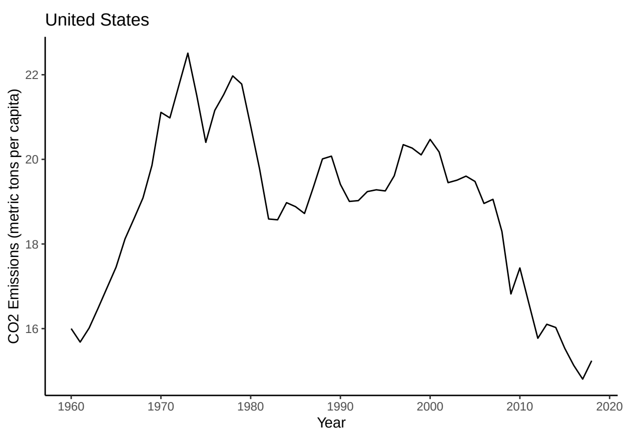
To have a more detailed view of each countries dioxide emissions we plot each time series plot individually.











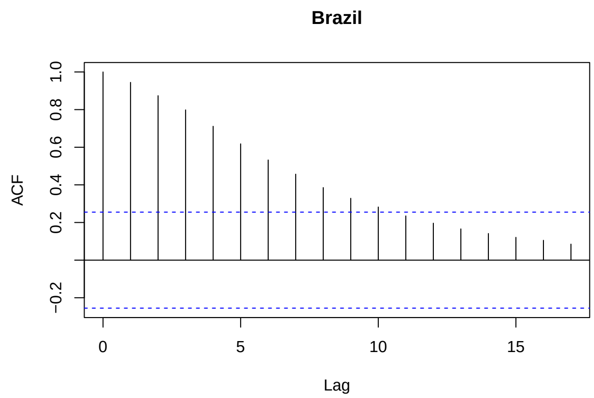
Plotting the time series individually makes it evident that all series aren't stationary, as they show different trends. In the case of Brazil, China and India, their emissions have been rising over the last 50 years and there is positive trend. In the EU and the US, the case is different, but they appear to be non-stationary.

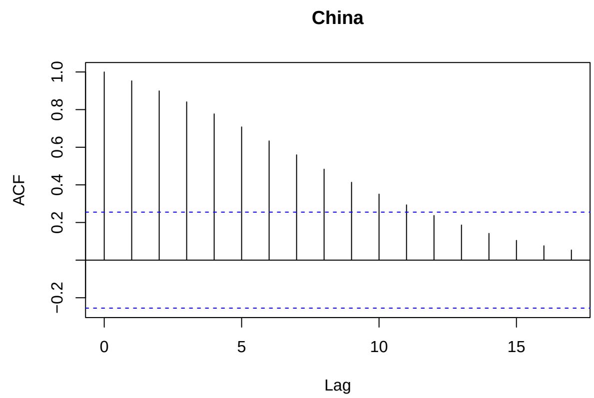
Autocorrelation plots and Partial Autocorrelation plots

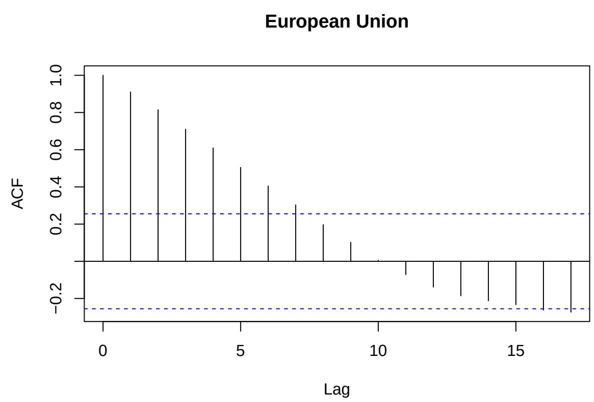
Using the autocorrelation function formula:

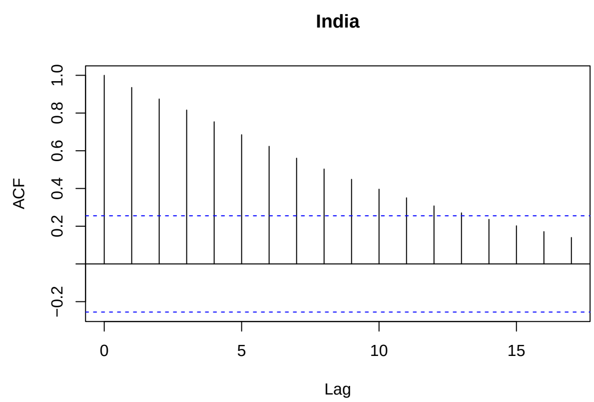
$$\rho_k = \frac{\gamma_k}{\gamma_o} = \frac{Cov[y_t, y_{t-k}]}{Var(y_t)}$$

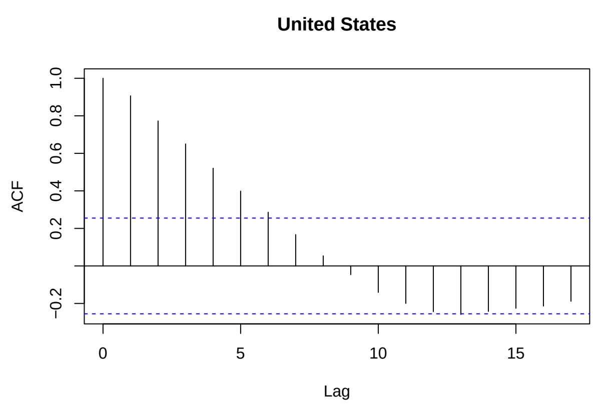
all ACF are calculated for each country group. This works as a visual way to determine if a time series object is stationary or not. In the next section we run the necessary test to confirm our findings from the ACFS.



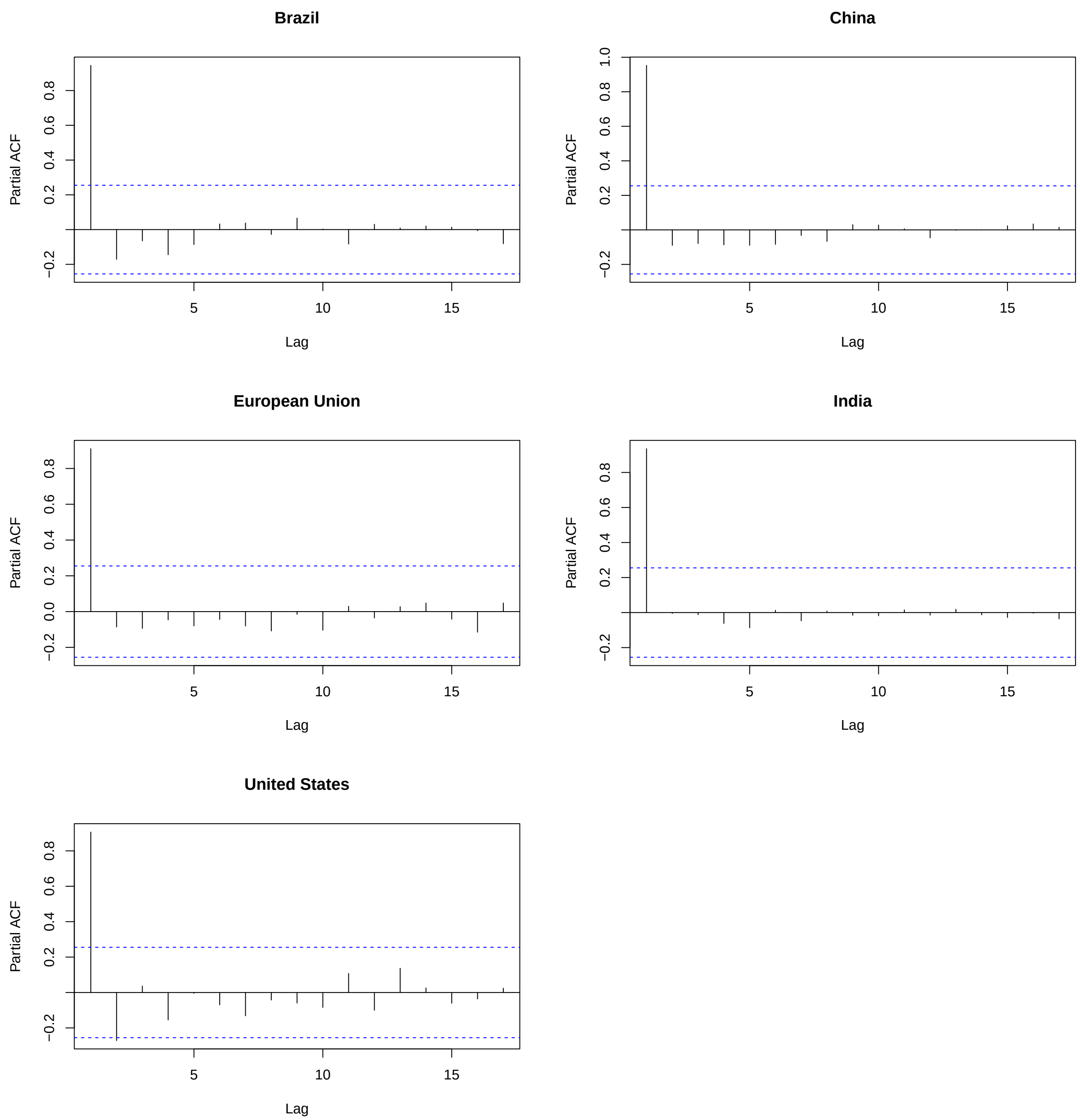








To further assist with our model choice, we use the Partial Autocorrelation Functions plots as well.


Brazil
China
European Union
India
United States
Partial ACF
Lag
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
5
10
15

Stationarity tests

Augmented Dickey Fuller Test

With this test we want to negate the null hypothesis that a unit root is present in an auto regressive model of a given time series, and that the process is thus not stationary.

A common rule of thumb for determining pmax, suggested by Schwert [1989], is

$$p_{max} = [12(\frac{T}{100})^{1/4}]$$

KPSS Unit Root Test

We also use the KPSS Unit Root test from Kwiatkowski et al. [1992] to test the H0 hypothesis of stationarity.

Table 2: p-values for ADF and KPSS Tests

	ADF p-value	KPSS p-value
Brazil	0.0359389	0.0208252
China	0.4486139	0.0248861
European Union	0.0064731	0.1000000
India	0.9751775	0.0209267
United States	0.1702564	0.1000000

Based on the table above , results from the Augmented Dickey Fuller Test and the KPSS Test, we can only reject the ADF H0 hypothesis of non-stationarity for Brazil and the European Union. On the contrary, KPSS p-values show that we might reject the H0 hypothesis of stationarity for Brazil, China and India.

Estimation and results

Having conducted the necessary test and evaluated al the different time series and their characteristics, it is time to estimate a model, present, analyze and interpret the results.

For the estimation of the ARIMA model we ran a so-called Grid-Search for the 5 different country groups and all possible combinations of models within our parameters. We then evaluate the best model for each country based on the Akaike Information Criterion :

$$AIC = log(\hat{\sigma}^2_\epsilon) + 2\frac{p+q+1}{T}$$

Having defined the maximal p order in the previous section (11 lags), we restricted the d order to 3, as too many differentiation of the time series don't bring better results. Moreover, we restrict the q parameter from the MA(q) model to 11.

Below there is a table with each countries' best models and their respective AIC coefficients.

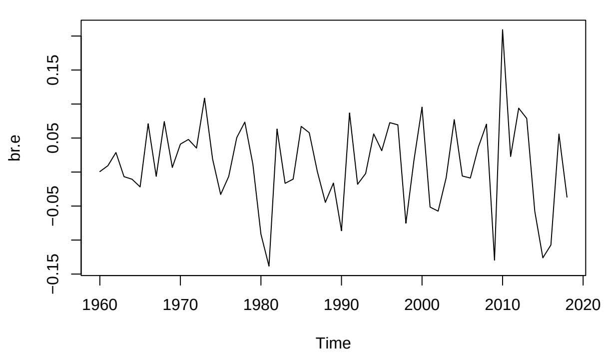
Country	Order	AIC
Brazil	(2,1,5)	-127.6029
China	(1,1,0)	-61.7693
European Union	(0,2,1)	10.93498
India	(1,1,2)	-254.3758
United States	(0,1,1)	98.9266

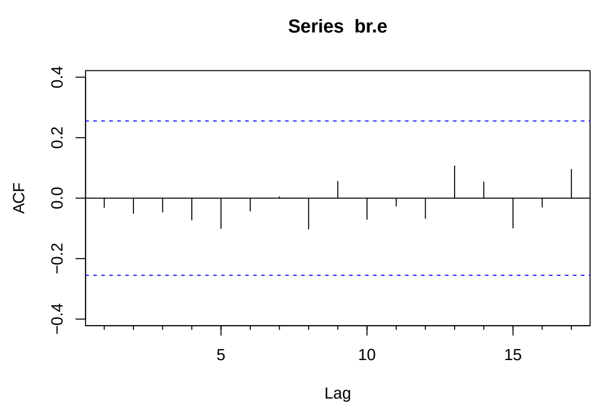
We compared the results with results from the **auto.arima** function from the *forecast* package, and they match for all the countries, although the **auto.arima** function required some extra tweaking. In the end, we choose the models that display the lowest AIC values.

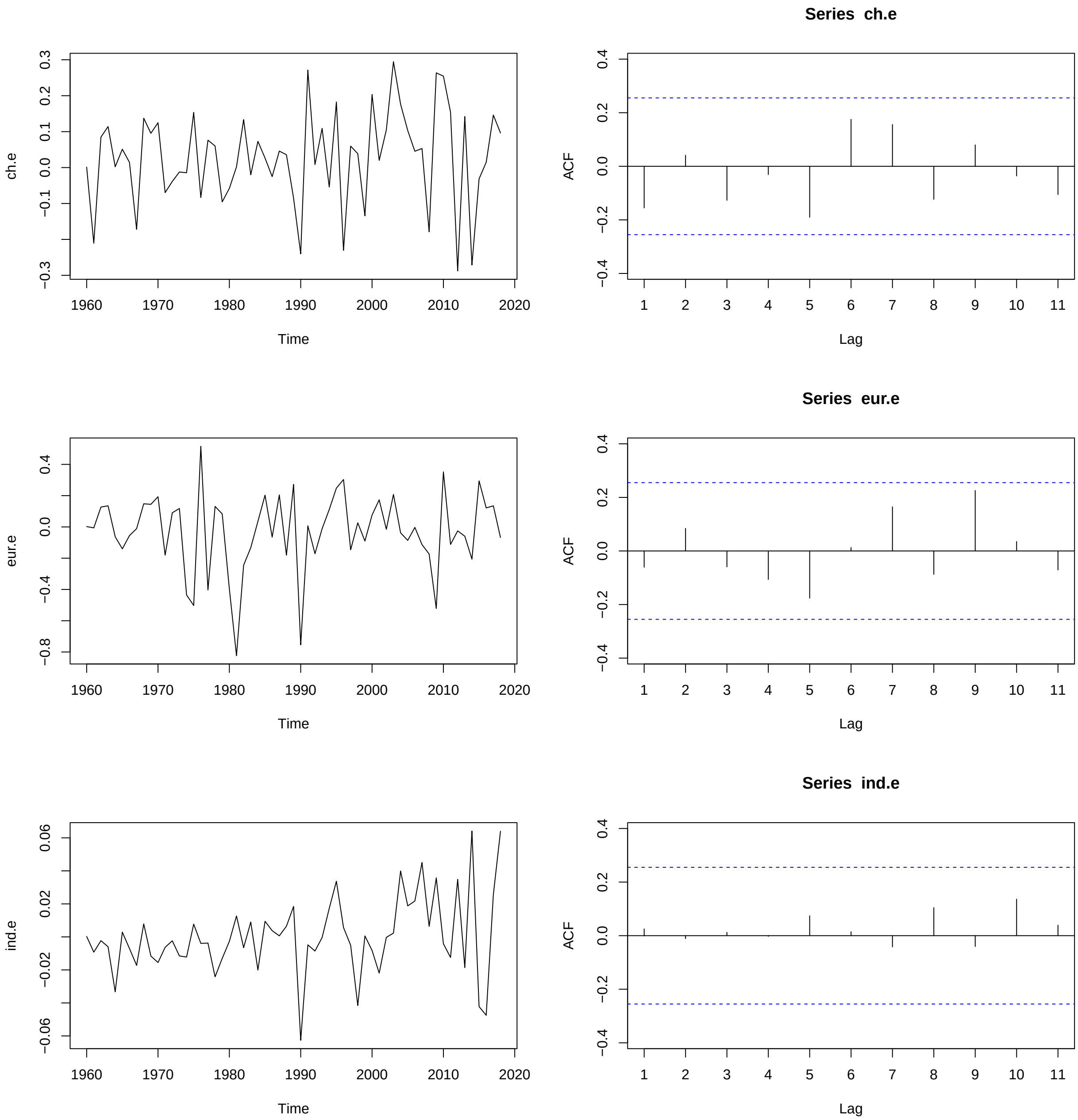
Diagnostics

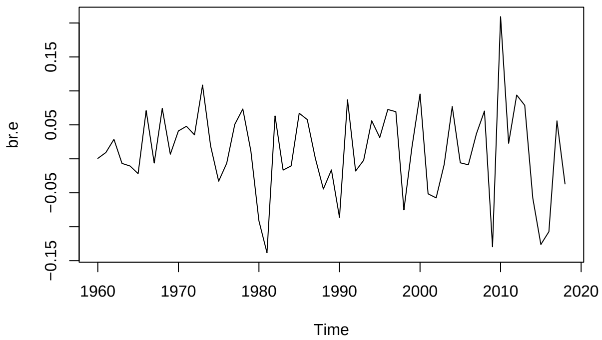
Next we proceed to run diagnostics of our models, that means that our model should capture the dynamics of the time series. Consequently, the residuals should be approximately white noise (No residual correlation, same variance, normally distributed). We do this with the Ljung-Box Test:

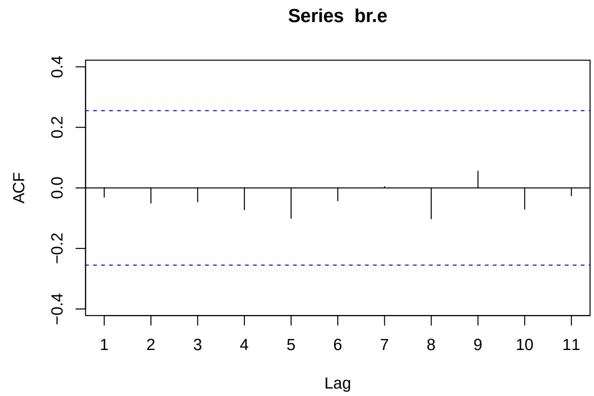
$$Q_K = T(T+2)\sum_{k=1}^{K}\frac{1}{T-k}\hat{\rho}^2_k \longrightarrow \chi^2(K-p-q)$$





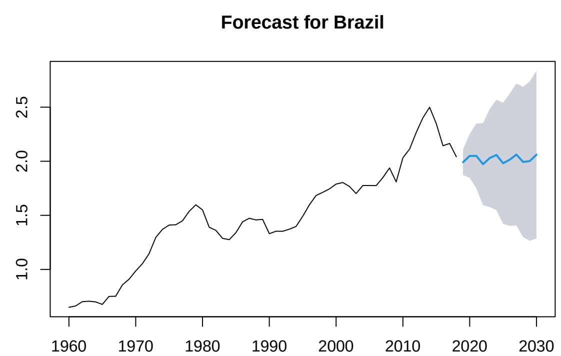

Series ch.e
Series eur.e
Series ind.e
ch.e
eur.e
ind.e
ACF
Time
Lag
1960
1970
1980
1990
2000
2010
2020

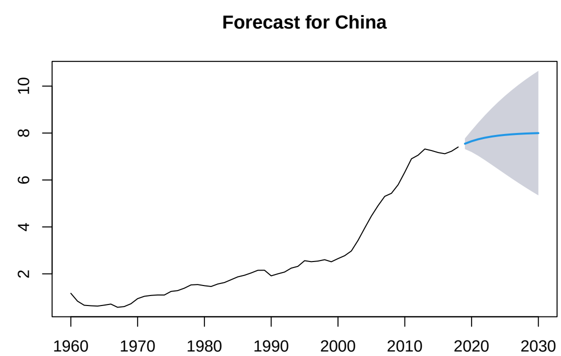


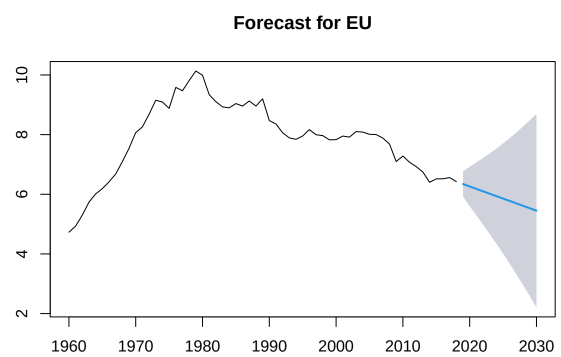


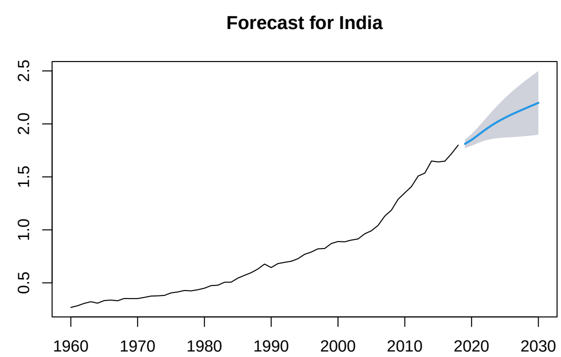
Forecast

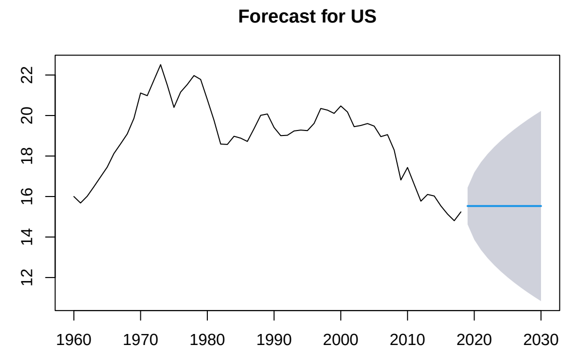
Finally, we proceed to forecast carbon dioxide emissions for each country group until 2030 based on each fitted ARIMA model.











The forecast for the different countries show somewhat different outcomes, in the cases of Brazil and the United States, prediction for the next 12 periods shows that the emissions will remain stable (within a 99% confidence interval). For the cases of China and India, the forecasted values show some worrying trends, by 2030 both of these countries will still show rising CO2 emissions, although China's trend seems to slow down a bit compared to the early 2000's. Luckily, the forecast for the European Union shows that by 2030, their CO2 emissions will resemble the ones from the 1960s.

Conclusion

To wrap up this paper we will review the process of the modelling, the estimation, the diagnostics and the forecasting of the different time series.

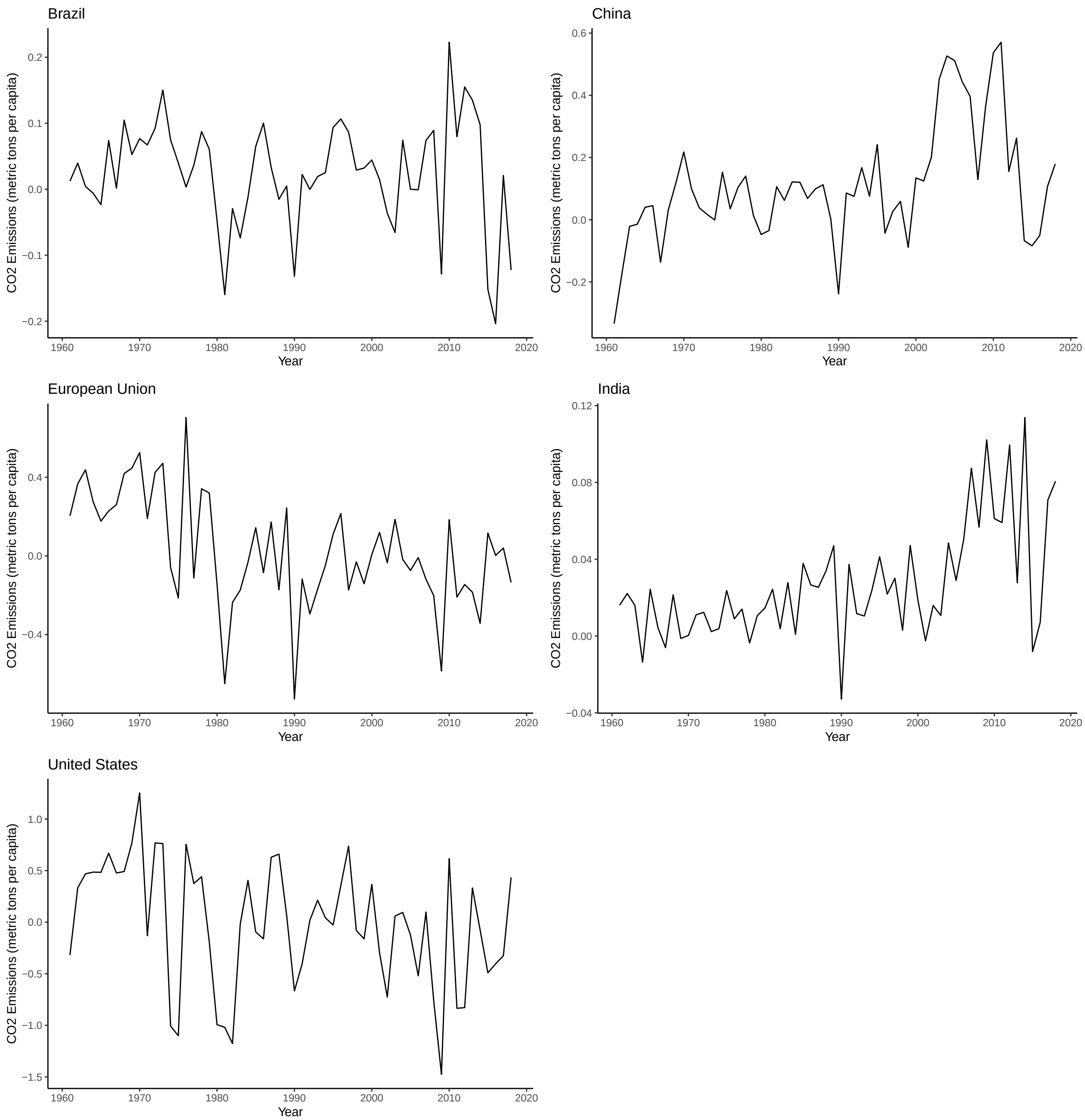
Summing up what has been done, we compared time series from 5 different countries or country groups, to analyze and model the CO2 emissions using ARIMA models. Each country shows a different trend, magnitude and volatily in the data, so different parameters and different models based on assumptions had to be fitted for each country. We used a variety of a Grid Search algorithm to navigate through different combinations of ARIMA (p,d,q) parameters as a way to support our initial stationarity tests and Auto Correlation Functions. In the end we chose each model based on the lowest AIC value for each country. Although literature on CO2 emissions is not particularly scarce, not many authors and researchers seem to use ARIMA models for this kind of forecasting. Probably there might exist another advanced techniques that better forecast CO2 emissions, for example the novel library *prophet* by Facebook, a collection of forecasting algorithms.

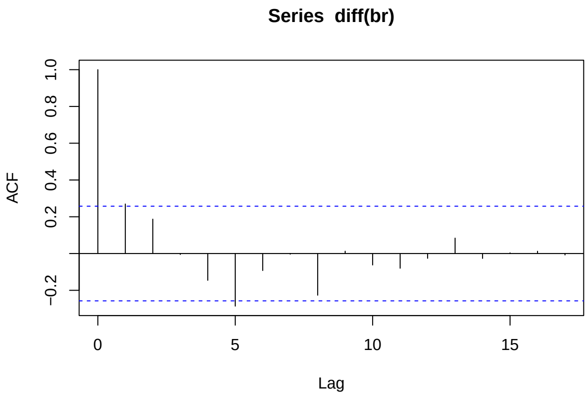
From an environmental point of view, the results and forecast of this study are negative, though United States and the EU have shown decreasing trends in their emissions, they are still the two biggest actors in the world. With China's surprisingly fast emergence in the global economy, the forecast for them shows the most worrying trend. China has already surpassed the EU's emissions and though they have somewhat slowed down the pace, they still show a rising trend. The main reason for including two other emerging economies like Brazil and India, was to check if China's disturbing trends also translate into these countries. Sadly for our environment, the answer is yes, albeit on a much smaller scale.

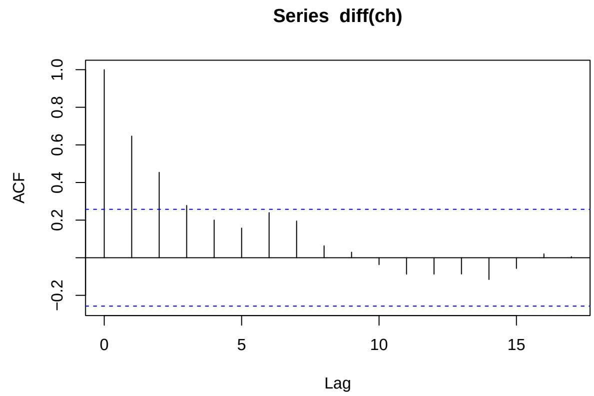
Some other factors that could prove to be pivotal in the slow decline of CO2 emissions in the European Union and USA could be historical events like the Kyoto Protocol in 1997 and the Paris Agreement in 2015, and some natural distasters, like the 2011 tsunami in Japan that caused the explosion in the nuclear factory in Fukushima. This event led to a chain of events that ended with Germany's (and some other European countries) abandonment of atomic energy.

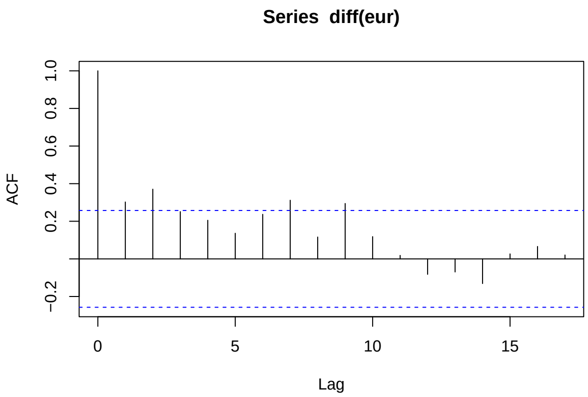
Appendix

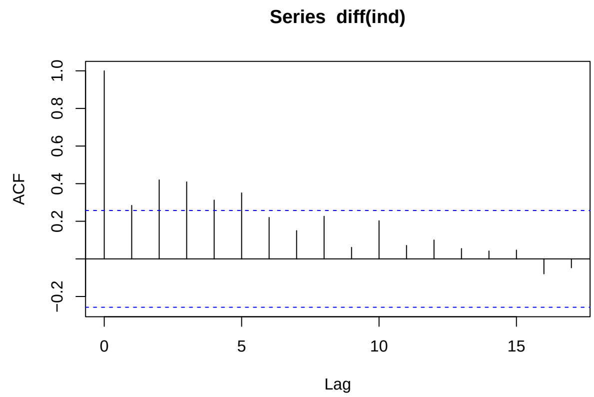
For sake of completeness, we include here the differenced plots of the time series and their respective ACFs.

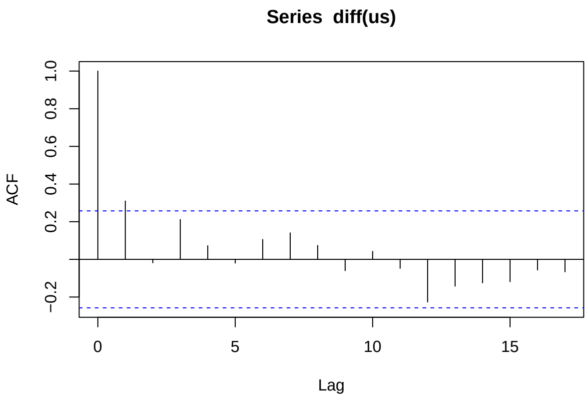



Series diff(br)
ACF
Lag


Series diff(ch)
ACF
Lag


Series diff(eur)
ACF
Lag


Series diff(ind)
ACF
Lag


Series diff(us)
ACF
Lag

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