UNIVERSIDADE DE LISBOA
ISEG - LISBON SCHOOL OF ECONOMICS & MANAGEMENT

MASTER
APPLIED ECONOMETRICS AND FORECASTING

MASTER´S FINAL WORK
DISSERTATION

ECONOMIC GROWTH AND ENVIRONMENTAL DEGRADATION: AN ANALYSIS ON GDPPC AND CO2PC EMISSIONS

INGRIDE STOUGE TARRAFA

SUPERVISION:
PROFESSOR NUNO RICARDO MARTINS FARROPAS SOBREIRA

DOCUMENT SPECIALLY MADE FOR OBTAINING A MASTER'S DEGREE

2021

"We are the first generation
to feel the effect of climate change
and the last generation
who can do something about it."
Barack Obama

ABSTRACT

The continuous growth in GHG emissions derived from human activity has stirred the debate on if it is possible to combine an ever-growing economy with sustainability values, environmental equality and justice. Whether climate change should be tackled from an eco-modernist perspective, or an economic de-growth perspective is important to help define future policy. Therefore, this MFW aims at estimating forecasted values of the GDPpc and CO2pc and conclude whether the theoretical framework of the Environmental Kuznets Curve holds for these series in a selected group of countries. With this objective, an empirical analysis was made on both series where it became apparent how big fluctuations in these variables might be related to the economies dependency on the industry and export of fossil fuels. Moreover, three different models frameworks were applied to these series, with all presenting evidence on good predictive capabilities. Through cross validation, a model was select that would best fit to the data, being that for all series the chosen model was an ARIMA. The forecasted values from these models are aligned with the perspective that is drawn from past values, but do not corroborate the EKC hypothesis, with an average increase in CO2pc emissions predicted for the USA, for example. Thus, allying strong environmental policy to prosperity and economic and social development should be of greater focus to countries worldwide.

KEYWORDS: Economic growth; CO2 emissions; Environmental Kuznets Curve.

RESUMO

O crescimento contínuo das emissões de gases com efeitos de estufa derivados da atividade humana tem agitado o debate sobre se é possível combinar uma economia em crescente com valores de sustentabilidade e igualdade e justiça ambiental. Se as mudanças climáticas devem ser enfrentadas através de uma perspetiva eco-modernista, ou uma perspetiva de redução do crescimento económico, é importante para ajudar a definir políticas futuras. Assim, este TFM visa estimar valores de previsão para o PIBpc e CO2pc e concluir sobre se o quadro da teoria da Curva Ambiental de Kuznets se verifica para estas séries de uma seleção de países. Com este objetivo, foi elaborada uma análise empírica sobre estas séries, na qual ficou aparente do quão as grandes flutuações destas variáveis poderão estar relacionadas com a dependência de uma economia da indústria e exportação de combustíveis fósseis. Além disso, três diferentes modelos foram aplicados a estas séries, sendo que todos apresentaram evidência de uma boa capacidade preditiva. Através de validação cruzada, um modelo foi selecionado considerando que se encaixaria melhor nos dados, sendo o modelo escolhido para todas as séries um ARIMA. Os valores previstos a partir destes modelos estão alinhados com a perspetiva que se obtém dos valores passados, mas não corrobora com a hipótese da Curva Ambiental de Kuznets, com um aumento médio nas emissões de CO2 previsto para os EUA, por exemplo. Assim, aliar políticas ambientais fortes à prosperidade e ao desenvolvimento económico e social devem ser de maior foco para os países em todo o Mundo.

PALAVRAS-CHAVE: Crescimento económico; Emissões de CO2; Curva Ambiental de Kuznets.

GLOSSARY

ACF - autocorrelation function

AIC - Akaike's information criterion

AICc - Akaike's information criterion corrected for small sample bias

AR - autoregression model

ARIMA - autoregressive integrated moving average model

BIC - Bayesian information criterion

CO2 - carbon dioxide

CO2pc - carbon dioxide per capita

DGP - data generating process

ETS - exponential smoothing

GDP - gross domestic product

GDPpc - gross domestic product per capita

GHG - greenhouse gases

KPSS - Kwiatkowski-Phillips-Schmidt-Shin

LS - least squares

ML - maximum likelihood

MA - moving average mode

PACF - partial autocorrelation function

MAE - mean absolute error

RMSE - root mean squared error

TABLE OF CONTENTS

Abstract iii

Resumo iv

Glossary v

Table of Contents vi

1. Introduction 7

2. Exploratory Data Analysis 10

   2.1. GDP per capita 10

   2.2. CO2 per capita 13

3. Model specification and estimation 16

   3.1. Linear regression model 16

   3.2. Exponential smoothing methods 19

   3.3. Box-Jenkins ARIMA model 20

4. Forecasting 22

5. Conclusion 24

References 26

Appendices 28

1. INTRODUCTION

Climate change has gained a lot of focus throughout the years, with a gathered consensus from the scientific community, governments, and citizens over its negative effects on human lives, the ecosystems and the economy. A report published in August 2021 by the United Nations Intergovernmental Panel on Climate Change, which analysed the findings of over 14,000 papers of climate science, exposed what has been known but also feared by many: "*Human influence has warmed the climate at a rate that is unprecedented in at least the last 2000 years*" and "*many changes due to past (...) greenhouse gas emissions are irreversible for centuries to millennia*". The link between the emissions derived from human activity and climate change is undeniable and we are responsible for the climate crisis that we are already living. In addition, it has become very clear that climate change comes with an increasing cost for society and the economy, especially for poor developing countries who depend heavily on natural resources and aren't equipped with infrastructures to adapt to sudden natural catastrophes. This perpetuates the injustice and inequality these populations face, undermining their potential to overcome national health issues and raise women empowerment (DARA 2010). Considering this, the debate revolving this issue is no longer whether climate change is real and should be considered a threat, but how it must be tackled in order to continue building prosperity without detriment to equality and justice.

Economists have been studying the influence of economic growth on the evolution of GHG emissions for decades now, with one of the most known studies being the one that introduced the concept of the environmental Kuznets curve. The Environmental Kuznets Curve establishes a relationship between the level of environmental degradation and economic growth, using various indicators and proxy variables such as GDP per capita, which is shaped as an inverted "U". This implies that in the early stages of economic growth, the level of environmental degradation increases until a certain level of GDP per capita is reached when this relationship becomes indirect and economic growth leads to environmental improvement (Grossman and Krueger 1991). On their study of the environmental impacts of a North American Free Trade Agreement, Grossman and Krueger indicate that a small economy relies mainly on technology which is highly polluting. This economy will gradually become more industrialized and subsequently reach a high level of income, which is equivalent to the highest level of environmental degradation. Regardless, this allows for investments on more efficient and sustainable industrial technology. After this point, a transition is expected in this economy, from a highly industrialized one to one where the industrial sector is less polluting, the tertiary sector is predominant and there's a higher demand for environmental protection, with a subsequent decline on the negative impact it has on the planet. This curve can help support the debate and development of policies to combat climate change, namely on the impact of structural economic changes in consumption or investment as available income increases. Nevertheless, the validity of this hypothesis has been tested with different results being obtained. While some studies have confirmed the existence of this relationship in countries in Western Europe and some in Asia (Li et al. 2016), others didn't find evidence that could corroborate it (Ozturk & Al-Mulali 2015, Stern & Perman 2003). Li, Wang and Zhao's paper showed evidence that supported the EKC hypothesis for carbon dioxide, waste water and waste solid emissions in dynamic panel models estimated with a system Generalized Method of Moments estimator. Ozturk and Al-Mulali proved that for Cambodia there is a linear relationship between GDP and increases in CO_2 emissions, but did not confirm the environmental Kuznets curve hypothesis. Stern and Perman found that even though cointegration is found between GDP and sulfur emissions for some countries, for most of these the relationship between both variables is not concave. Additionally, those that do find empirical evidence of this relationship studied other pollutants such as nitrogen oxide or sulphur dioxide which appear to confirm it better than CO_2 emissions do (Stern & Common 2001, Shikwambana et al. 2021, Grossman, G. M. & Krueger, A. B. 1995). Stern and Common demonstrated that for economies with high levels of per capita income, an inverted "U" shaped function of GDP per capita and sulphur dioxide emissions is estimated. Kganyago, Mhangara and Shikwambana showed that in South Africa there is correlation between GHG emissions and economic growth. However, the EKC hypothesis was not confirmed as the carbon and sulphur dioxide series presented an "N" shaped curve. Even Grossman and Krueger found the same results for different derivatives of pollution. All in all, it can't be said with a high degree of certainty that this relationship holds for different economies. In the cases where it doesn't, the best way forward might be to combine economic growth with policy packages and regulations that ensure the transition of the economy to a sustainable one.

With this in mind, the objective of this MFW is to assess which models fit the best to the GDP per capita and CO_2 per capita series, have the best predictive capacity and analyse if the prediction values and intervals obtained from them follow EKC theoretical framework. We benefit from analysing the data from different countries against one another, thus a broader approach was taken and several economies were chosen considering a few quantitative and qualitative dimensions, such as GDP level and growth rate, population, historical and political characteristics, and other socioeconomic indicators, for comparison purposes. An emphasis is made on countries with the largest and most industrialized economies, the fastest growing economies, and a few cases of interest. Following the principles from the environmental *Kuznets* curve, large economies such as the United States or China should be following a declining trend in the indicators of their impact on the climate, and the ones in development or following a growth trend in GDP should see their GHG emission levels steadily increasing, considering this measure as a proxy for environment degradation. To demonstrate this theorem we should forecast this series and evaluate whether their future behaviour for each type of economy follows the expected behaviour pattern, if the EKC hypothesis holds.

In the initial analysis made on both the GDP_{pc} and $CO_{2_{pc}}$series, it becomes clear that there might be a relationship between the characteristics of a certain economy, namely how it's industry is constituted, and the behaviour of these series. Countries who depend heavily on fossil fuel extraction and exports present significant fluctuations throughout time that align with periods where significant events or changes occurred in this sector of their economy. This includes countries in the Middle East, African economies, and territories in Eastern European. Additionally, China figures itself has a case of interest because of the relative size of its economy and for being the highest-level polluting country in the world. When estimating trend linear regression models for these series we see that, considering the adjusted R^2 statistic and individual statistical significance tests, these models do not fit well into our data, even though the plots produced seem to follow the past behavior of the series accurately. Regardless, from the testing done on the residuals of the models estimated we conclude that these models will likely produce forecast with adequate prediction intervals, as they do not present serial correlation in their errors. As for the exponential smoothing methodology, for all the series in study one of two models were selected from the information criteria scores obtained: simple exponential smoothing model with additive errors or Damped Holt's linear method model with additive errors. Moreover, after confirming that the transformed series analysed were in fact stationary, we selected ARIMA models to fit these series. For the case of China's GDP_{pc}, this model selection was done manually and selected an ARIMA(2,0,3). For the remaining economies analysed, an automated algorithm was used to select the ones with the lowest information criteria score. Both GDP_{pc} and $CO_{2_{pc}}$ series for the USA seemed to follow an ARIMA(0,0,1), and for Kuwait's and Qatar's series for GDP_{pc} and $CO_{2_{pc}}$ respectively the selected model was an ARIMA(0,0,0). Finally these three selected models were compared in their accuracy in forecasting, resorting to the MAE and RMSE, and for all countries an ARIMA model was selected, being this a good indication that these series may be best fitted by a model with more dynamic regressors. Nonetheless, the forecasts produced help establish that the EKC curve hypothesis does not hold for the countries in study. Thus, it remains of the biggest importance to deepen governments focus on policies that minimise the environmental costs of economic growth. To sum up, this MFW follows the methodology described by Rob. J. Hyndman and George Athanasopoulos in their online textbook "Forecasting: Principles and Practice (3rd ed)". On the following chapter we are going to study the time series for GDP_{pc} and $CO_{2_{pc}}$ emissions for a set of economies and regions, analysing statistical measures on the data available for both series empirically and in a graphical manner. Secondly, we specify different univariate models for these series, checking these model's performances through specification testing and error analysis, in order to assess their usability for forecasting. Finally, the model selection for each series is done through cross-validation and the forecasted values for each selected model are produced. To conclude, an analysis is made on these values for a selected group of countries and some conclusions are drawn on the applicability of the Environmental Kuznetz Curve to these countries in study.

2. EXPLORATORY DATA ANALYSIS

2.1. GDP per capita

The data analysed was taken from the Maddison Project Database 2020, which includes data on the real gross domestic product per capita in 2011 base year pricing levels for dollars. We have a varying number of observations for 169 countries, ranging from year 1 to 2018 - an irregular series -, in addition to regional decade totals for 8 regions of the world. We are analysing this series in its first difference of the logarithm transformation, $(1 - B)\log(GDP_{pc})$, where B is the backshift operator, which allows to follow how the GDP_{pc} has changed percentage wise throughout the years for each country or region. Firstly, we will look at a few essential features of the series such as its mean, maximum values, minimum values, and quantiles. Looking at a ranking of all 169 countries' mean (Figure 1) we see that we have a very differentiated group of countries, from different regions and with different levels of GDP_{pc}. In the number one position is Kuwait, with an average year to year change in the GDP_{pc} of 4.3%, followed by Malta in a close second place with an average change in GDP_{pc} of 4.28%. The data implies that these economies are the most volatile even though they have very different characteristics - Kuwait's economy is heavily based on fossil fuel exports but Malta is dependent mainly on foreign trade and tourism. The top 4 also includes Libya and Saudi Arabia, with a mean growth of 4.22% and 3.72% respectively, which can be "grouped" with Kuwait in the category of economies that are mostly constituted by the petroleum export sector. Looking at this ranking from the bottom up (Figure 2) we see that, apart from the Syrian Arab Republic, the bottom 10 is mainly constituted of African countries. All of them have an average negative growth rate for GDP_{pc}, which is a clear indicator of their level of development (or lack thereof). The case of the Syrian Arab Republic is easy to explain as this territory has witnessed tumultuous periods of political and social disasters, including military coups and civil war. By analysing the quantiles (Figure 3), we get the minimum and maximum values for each economy, that is, the years when there was the biggest or lowest yearly change in GDP_{pc}. To no surprise, Kuwait is the country with the highest GDP_{pc} registered growth rate, with a 261% increase in GDP_{pc} in the year 1948. If we analyse the maximum yearly growth rates for each decade, we can observe that the leading group of countries varies greatly throughout the 20th century. Portugal enters the top 10 ranking in the decade of 1930 (Figure 4), with a growth rate of 14.3% in 1937. A pattern that seems to be persistent throughout the years and across economies is their volatility, since we don't see an increase on the number of countries whose minimum value is positive as the decades go by. After 2011 and until 2018 (Figure 5), only Turkmenistan shows to not have registered a decrease in GDP_{pc}. After viewing how the data is structured, we can do a graphical analysis of the series for a few countries, which allows to better identify trends and changes over time. Plotting the $(1-B)\log(GDP_{pc})$ for China (Figure 6) gives us a graph with a few missing observations but a lot of information about how this series has evolved in the second half of the past century. On average, China's GDP_{pc} has varied 4.11% yearly (Figure 7) and the series follows a positive trend. We detect some volatility in China's economy between the 1950s and 1970s, with big fluctuations from period to period which may be attributed to the *Great Leap Forward*, an economic program aimed at massively multiplying agricultural outcome but resulted in demographic disaster, with 55 million deaths attributed to famine. Nevertheless, these decades were followed by a more robust and steady evolution of the GDP_{pc} in the final quarter of the century. This change in behaviour was due to what has been named as the *Opening of China*, a series of economic reforms intended to increase the country's wealth and decrease poverty. When looking at the graphical representation of this series for the US economy (Figure 8), we also detect a change in behaviour. With an average growth rate of 1.63% (Figure 9), the United States went through a long period of big fluctuations in GDP_{pc}, which includes both World Wars. These same patterns are observed for the series of European countries such as France, Italy or Germany (Figure 10). In 1934, this USA series registered its largest mean shift the series of 10.1% (Figure 11). But nationwide applied economic stabilization instruments such as fiscal and monetary policies directed the economy to the steady growth path which it is known for today. In addition, in the plot shown we can clearly identify the financial crisis of 2008, when GDP_{pc} decreased on average 1.24% (Figure 12). Being one of the world's richest countries in the world, Kuwait is also a country worth examining (Figure 13). Kuwait holds roughly 10% of the world's crude oil reserves, which account for half of this countries' GDP, making it highly susceptible to variations in barrel prices. In the 1970's, the country benefited from a dramatic inflation of these prices which consequently led to a 38.1% increase in GDP_{pc} (Figure 14). Nevertheless, in 1992 we observe the most dramatic shift in the mean of this series when GDP_{pc} increased by an average of 72% (Figure 14). This occurrence was a consequence of the reconstruction of the country from the Iraqi invasion and occupation in 1990. Even though the wealth of the country was severely damaged from the Gulf War - 749 of Kuwait's oil wells were destroyed - a $5 billion effort to repair the damaged oil infrastructures of the territory allowed for a restoration of its prosperity. Finally, looking at the data we have for 8 regions of the world

(Figure 15) we see that East Asia has the largest average decade growth rate for GDP_{pc} at 24.8% followed by the Middle East with 21.5%. On the last spot of the ranking is the Sub-Sahara African region with an average decade growth rate for GDP_{pc} of 11.7%. Additionally, the Eastern Europe region holds the maximum growth rate registered with an increase in GDP_{pc} from 2000 to 2010 of 63.9% (Figure 16). This ranking displaying economic growth is an accurate representation of the economic development level of each of these different regions, as one can associate a growing GDP_{pc} with high levels of industrialization of an economy, availability of infrastructures and low poverty levels, amongst other measures of socioeconomic wealth

2.1. CO2 per capita

The data analysed was taken from a data package named "Global, Regional and National Fossil-Fuel CO_2 Emissions: 1751-2017" and is a time series of per capita fossil-fuel carbon dioxide (CO_2) emission rates by country from 1751 to 2017. The given national estimates of per capita CO_2 emissions (${CO_2}_{pc}$) are expressed in metric tons of carbon and include emissions from solid, liquid and gas fuel consumption, cement production, and gas flaring. This data was generated using the United Nations Energy Statistics database and the United States Geologic Survey's cement statistics and serves as the base for the annual global carbon budget published by the Global Carbon Project. Similarly to the previous section of this MFW, we are analysing this series in its first difference of the logarithm transformation, $(1 - B)\log({CO_2}_{pc})$, which allows to follow how the ${CO_2}_{pc}$ has changed percentage wise throughout the years for each country. Firstly, we will look at the summary features of this series, following with some graphical analysis. If we compare the group of countries that are in the top spots of the mean's ranking for this series (Figure 17) with the ones from the GDP_{pc} series, we can see that its composition is very different. If we disregard a few territories that present high mean values considering their population size, we notice a few countries that do not have high levels of GDP_{pc} but present high average yearly ${CO_2}_{pc}$ emissions. For example, Serbia, Estonia and Ukraine are in the top 10 countries with the highest average of ${CO_2}_{pc}$ emissions yearly growth, with 17.6%, 15.7% and 13% respectively. What these 3 economies have in common is that the mining industry constitutes an important part of their GDP. In the case of Serbia, their lignite coal reserves are the 5th largest in the world and 71% of the electricity produced in the country comes from thermal-power plants (meaning power plants that burn fossil fuels). As for Estonia, it is one of the few countries in the world, alongside China and Brazil, that mines and processes oil shale rock. This highly polluting industry has raised air and water pollution levels for this country since it was implemented in the 1950s. Lastly, Ukraine is one of the world's main producers of minerals, even though only half of its 8,000 known mineral deposits are currently under exploration. Georgia completes the top 10 of this ranking, but it is unclear why their average $CO_{2_{pc}}$ emissions growth is so high. According to the International Energy Agency, most electricity consumed in this country is produced by their national hydroelectric facilities, a sustainable energy source. Furthermore, there are a few notable mentions worth making (Figure 18) such as China who holds a 5.73% average yearly $CO_{2_{pc}}$ emissions growth rate, Saudi Arabia and Kuwait who presented a high average GDP_{pc} growth rate register an average of 3.51% and 3.47% growth rate for yearly $CO_{2_{pc}}$ emissions, respectively, and Portugal who also has a positive average growth rate of 3.03%. Apart from this there are a few developed economies that follow an average negative trend in their $CO_{2_{pc}}$ emissions, including the United Kingdom and the United States. This raises the question of whether this is the result of these countries' environmental policies. In addition to this, even though the Scandinavian territories are known for their efforts towards more sustainable communities and businesses, only Sweden has a close to 0 average yearly $CO_{2_{pc}}$ emissions growth rate. Regarding the maximum values for this series (Figure 19), we see that United Arab Emirates takes a high spot of the ranking with a staggering 360% yearly increase in per capita CO_2 emissions registered in 1967, which is around the time their crude reserves were discovered and extraction and exports catapulted. Qatar is currently the country with the highest level of per capita CO_2 emissions and in 1963 registered one of the highest growths in this indicator, of 338%. This astounding fluctuation resulted from the start of their emissions from gas flaring, resulting from oil and gas extraction, when massive investments were made in extraction installations. In the same way, the Islamic Republic of Iran had a 240% increase in per capita CO_2 emissions in 1955, after a rapid increase in production for export of oil and its derivates. Just as we did for the GDP_{pc} series, looking at the maximum yearly growth rates for each decade we can observe that the group of countries that constitute the ranking differs from one decade to the next one, with a few countries remaining in the frontlines as the biggest polluters per capita. If we disregard a few small territories, we can spot a few interesting appearances. In the 1960's, Singapore recorded a 146% increase in $CO_{2_{pc}}$ emissions (Figure 20) which followed the country's independence, consequent increase of public spending on infrastructure, and growth in foreign investment in the territory, becoming very quickly the central market for oil in Asia. In the 1970's, Greenland registered an increase of 119% in their emissions (Figure 21). It figures itself has a surprising measure, considering the characteristics of this economy. Yet, an unprecedented decrease in population numbers combined with an increase in liquid fuel consumption seem to have been the trigger for this behaviour in the series. Furthermore, in the 21st century Angola has become the leading exporter of petroleum crude in the Sub-Saharan Africa region. After the end of a civil war that lasted 27 years and with the help of the Chinese, the country invested heavily in their mining and extraction infrastructure, making its economy highly dependent on these products exports. In 2004 this meant 65.7% more CO_2 emissions were produced per capita in comparison with the year before (Figure 22). To finalize the analysis over these figures, we look at Mozambique that in 2014 registered an 81.1% increase in $CO_{2_{pc}}$ emissions (Figure 23). To no surprise, Mozambique is rich in natural resources and in 2011 the discovery of big gas reserves led to a rise in foreign investment in processing infrastructures, but also on accessibilities such as railways, that have boosted the industry into world relevance and have had a small impact in the development level of this country which is one of the world's poorest. With a clear picture of how this series has changed over the years, we can particularize our analysis by looking at its graphical representation for a few relevant economies. As previously mentioned, Qatar has the highest $CO_{2_{pc}}$ emissions level as of 2017, and the highest growth rate registered until this year is very obvious from the plot of this series, registered in 1963. The graph for $(1-B)\log(CO_{2_{pc}})$ obtained (Figure 24) doesn't give much information other than the growth trend of the CO_2 emissions for this country has remained relatively stable in the past half century, with an average 1.5% yearly increase (Figure 25). The graph for the Russian Federation series however follows an interesting pattern (Figure 26), very closely mimicking the behaviour of the GDP_{pc} growth rate. Until 1999 both these measures were in decline - on average, $CO_{2_{pc}}$ emissions vary yearly -0.478% (Figure 27) - until a growth trend was set and is still verified today. One exception is the year 2009 when for a brief period this economy went through a crisis dubbed the *Great Recession*, mainly because of an unprecedented fall in the price of the country's oil. This drastic change very clearly represents this country's dependency on the exports of fossil fuels. Finally, Sweden follows a decreasing trend in $CO_{2_{pc}}$ emissions (Figure 28), with an average yearly variation for this series of -0.0405% (Figure 29). In the past 50 years more times than not this series has varied negatively, which can be representative of the rising importance that hydropower, windpower and bioenergy have on this economies' energy consumption and exports - 52.6% by 2014, according to Eurostat. Moreover, in 2016 the Swedish government signed a deal with the opposing parties to reach 100% renewable electricity production by 2040.

3. MODEL SPECIFICATION AND ESTIMATION

3.1. Linear regression model

Considering the data that is in study in this MFW, we are going to analyse how the linear trend model fits to the GDP_{pc} and $CO_{2_{pc}}$ series. Firstly, for these model's estimation we assume that there is a linear relationship between the dependent variable and the regressors (in this case GDP_{pc} and $CO_{2_{pc}}$ and a $trend$) and the errors u_t have the following characteristics: a) they follow a Normal distribution, with zero mean and constant variance, $u \sim N(0, \sigma^2 I)$ b) they are not serially correlated, $E(u_t u_s) = 0, \forall t, s$(=1,2,..., T), c) they are not correlated with the model's regressors, $E(u_t|\boldsymbol{X}) = 0, t = 1,2, \dots, T$. Only under these assumptions can we estimate these models, $(1 - B)\log(GDP_{pc}) = \beta_0 + \beta_1 trend + u_t$ and $(1 - B)\log\left(CO_{2_{pc}}\right) = \beta_0 + \beta_1 trend + u_t$, with an unbiased Least Squares estimator ($\hat{\beta} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'$y), allowing for valid inference results and efficient forecasting (Wooldridge 2013). In that case, we can look at the output of the estimation for a few countries already analyzed in the previous chapter where we see the fitted values for each series, as well as a few important statistics. Looking at the results obtained for the Chinese GDP_{pc} (Figure 30), we see that the fitted regression has a positive slope which reflects the positive relationship between the $trend$ and GDP_{pc}.

The coefficient obtained for the $trend$ has statistical significance at 1% and shows that there is an upward trend of 0.06% increase in GDP_{pc} per year. Additionally, as a way of getting a hint at how well the linear regression fits the data, we can look at the R^2 statistic, more specifically to the adjusted R^2. In this context, we look at the second statistic as a better measure of the predictive ability of the model because the R^2 will overfit to any new variable that is added to it, whether its relevant or not. Maximizing $\bar{R}^2 = 1 - (1 - R^2)\frac{T-1}{T-k-1}$, where k is the number of regressors, is equivalent to minimizing the standard error of the equation, $\hat{\sigma}_e{}^2$(Wooldridge 2013). Considering this, we see that for the Chinese regression we have $\bar{R}^2 = 0.06159$, which is not a tolerable result. Following, the estimation for the USA GDP_{pc} (Figure 31) returns a regression with a very subtle upward trend for this variable, reflecting a near 0% increase in GDP_{pc} on average. However, not only is the $trend$ not statistically significant but also the estimated $\bar{R}^2$ calculated is very close to 0, denoting that a linear regression model does not seem to fit well to this series. As for the economy of Kuwait (Figure 32), despite the big positive fluctuations registered throughout the last decades, the fitted model presents a negative relationship between the $trend$ and GDP_{pc}, with an average yearly decrease in GDP_{pc} of 0.2%. As we did for the USA series, considering the results obtained from this estimation for the regressor significance test and adjustment test, we can evaluate this type of model as not suitable for forecasting the Kuwait GDP_{pc} percentual change series. Furthermore, we can also evaluate whether the estimated regression models fit to the time series data in study properly by verifying if the residuals follow the assumptions that we set in the beginning. For example, if we verify that there is autocorrelation in the residuals of the estimated models, we will likely produce forecasts with larger prediction intervals than needed, making forecasting inefficient. For this purpose we make use of Ljung-Box tests to analyze the presence of serial correlation until a set order p, aiming to test $H_0: \rho_1 = \rho_2 = \cdots = \rho_p = 0$ vs. $H_1: \exists \rho_j \neq 0$, where ρ_1, ρ_2, ..., ρ_p are the correlation coefficient's of the errors until a set order p. The statistic recommended by Ljung and Box for these tests is $Q^* \sim \chi^2_{(p)}$ (Hayashi 2000) which gives some importance to the choice correlation order: overall, p cannot be too small because the test will not detect autocorrelations of higher order, nor can't be too big because the test will lose power. With that being said, both the regression for China and the USA give us low p-values for this test (Figures 33 and 34), meaning the calculated statistic is statistically significant at a 5% level and we have evidence to reject H_0. We can see from both ACF plots that the residuals show significant spikes at lag 3 and 10 for China and lag 10 for USA. However, the autocorrelation isn't particularly large and will likely not have an impact on forecasting. For the Kuwait series (Figure 35), we do not detect any sign of serial correlation of the errors in the ACF plot and the p-value for the Ljung-Box seems to confirm that evidence. For the $(1 - B)\log\left(CO_{2_{pc}}\right)$ regression, we begin by estimating the series of Qatar (Figure 36) which gives us a linear regression with a decreasing trend of 0.12% in $CO_{2_{pc}}$ every year, on average, despite the maximum values presented in a few recorded years. The model estimated doesn't have a statistically significant $trend$ regressor and the estimation for the $\bar{R}^2$ is very low, which leads us to believe this type of model may not have good predictive ability. Similarly, the trend estimated for China's regression also follows a downward behavior (Figure 37). On average, China's $CO_{2_{pc}}$ emissions decrease 0.12% yearly. The same results are obtained in terms of regressor significance and adjustment to data, with the $\bar{R}^2$ of 0.018 being an undesirable result. Finally, the adjustment to the USA series fits a negative relationship between the countries $CO_{2_{pc}}$ emissions and time, this time this trend being a bit more apparent in the regression plot (Figure 38). Here we have a yearly variation of -0.04% of the USA's $CO_{2_{pc}}$ emissions, on average. This regressor is in this case significant at a 1% level. The model however does not adjust well to the series, with a very small calculated $\bar{R}^2$. Regardless, its important to complete this analysis with the inference on these models' errors serial correlation. In the case of Qatar (Figure 39), looking at the ACF plot we see one spike at the 11th lag which shouldn't be relevant to disturb the models effective forecasting. The Ljung-Box test performed gives us a high p-value, allowing us to not reject H_0 and to have evidence that there is no serial correlation on the errors of this model. Secondly, the test performed for China's model calculates a p-value that is very close to 0 (Figure 40). In this case we have evidence to reject H_0 and to believe that the errors of the model have serial correlation in one of the lags. Looking at the ACF plot we detect a spike at lag 9 which shouldn't interfere with the quality of the forecasts produced. Finally, for the American series we have a similar output with the one obtained for Kuwait (Figure 41). The Ljung-Box test performed gives us a hint that the is no error autocorrelation which can be confirmed by the ACF plot presented.

3.2. Exponential smoothing methods

Exponential smoothing methods when applied to forecasting are very advantageous, because with them we weight the most recent forecast observations produced with a higher associated weight and these weight's magnitude exponentially decreases as observations get older, $\hat{y}_{T+1|T} = \sum_{j=0}^{T-1} \alpha(1-\alpha)^j y_{T-j} + (1-\alpha)^T l_0$, where l_0 is the first fitted value at time 1 . Not only can the different type of statistical models that represent the underlying DGPs for the forecasts distributions generate identical point forecasts but also their own prediction intervals. Generally these models that follow this framework can be divided into two types: models with additive errors and models with multiplicative errors. We can obtain the same point forecasts using any of these models if the chosen smoothing parameter values α and l_0 are equal. Furthermore, these models should represent not only how the observed data changes over time but also its unobserved components such as level or trend. Alternatively to the linear regression model where we estimate the parameters of said model by minimising the sum of the squared errors, for the exponential smoothing models we estimate our parameters by maximizing the likelihood (or probability) of the data that results from the specified model (in particular, the unconditional log-likelihood function which is the logarithm transformation of the density function of $y|\boldsymbol{X}$) (Wei 1994). In this context, we obtain the same results as the ones from the LS estimation for the additive errors models if we assume normality, $y|\boldsymbol{X} \sim N(\boldsymbol{X}\beta, \sigma^2\boldsymbol{I})$, and the other assumptions described in the previous part of this MFW, but not for the multiplicative error models. What distinguishes LS from ML estimation is the estimator for the variance, which for ML estimation is $\sigma^2 = \frac{T-K}{T} s^2$. With this in mind, we can and must use information criteria to select the models that best fit to our data, including the AIC, AICc and BIC statistics, namely by selecting the information criteria whose score is the lowest. Considering that models with multiplicative errors aren't stable when they are fitting data with zeros or negative values, we choose to not consider these types of models in our estimation. Firstly, we start with our transformed GDP_{pc} series for China with the regression of 3 ETS models (Figure 42): Holt's linear method model with additive errors, ETS(A, A, N); Damped Holt's linear method model with additive errors,

$\mathrm{ETS(A, Ad, N)}$; and simple exponential smoothing model with additive errors, $\mathrm{ETS(A, N, N)}$. The method popularized in 1957 by Charles Holt includes an equation for the forecasts, as well as two smoothing equations - a level equation and a trend equation -, now making the forecasts a linear function of the steps-ahead h unlike what we have for simple exponential smoothing. The "damped" version of this method includes a damping parameter φ which smooths the trends into a flat line for further in time forecasts. Comparing the three models estimated we see that the $\mathrm{ETS(A, N, N)}$ has the lowest score for all information criteria presented and it's therefore the selected one for this series, with an estimated smoothing coefficient for the level $\hat{\alpha} = 0.0001$ and $\widehat{l_0} = 0.0411$. The fact that $\hat{\alpha}$ is very small indicates that more weight was given to observations that are more distant in time, resulting in a very stable and smooth series of fitted values. The same methodology was implemented on the transformed GDP_{pc} series for the USA (Figure 43), with the model selected being also $\mathrm{ETS(A, N, N)}$. Likewise, the estimation for α is also very small, allowing for the same conclusion to be drawn over the fitted values. As for the series for Kuwait, out of the three possible models the one with the lowest score throughout was the damped method, $\mathrm{ETS(A, Ad, N)}$ (Figure 44). For this case, two smoothing parameters are estimated, with $\hat{\varphi} = 0.8$ being previously selected: $\hat{\alpha} = 0.0274$, a relatively low value for the parameter, demonstrating a low trended series; and $\hat{\beta} = 0.0140$, the smoothing coefficient for the slope also with a low value, further suggesting the same conclusion. Additionally, we can implement this methodology of model selection for the $CO_{2_{pc}}$ series. Doing so for these series from Qatar and USA gives us similar outputs (Figures 45 and 47), as in, the same selection derived from the scores obtained. In both cases, the selected models were the simple exponential smoothing models with additive errors. Also common to both series is the low estimation for the smoothing parameter α, implying that the level and subsequently the trend don't have big fluctuations. On the contrary, for the Chinese series the select model is $\mathrm{ETS(A, Ad, N)}$ with $\hat{\varphi} = 0.8$ (Figure 46), but also with close to 0 estimations for the smoothing parameters.

3.3. Box-Jenkins ARIMA model

Besides exponential smoothing models, Auto Regressive Integrated Moving Average models (of order (p, d, q)) popularized by Box and Jenkins are also often applied to forecast time series to best describe the correlation relationships between the observations in data. As the name indicates, these models are composed by an autoregressive component of order p, including a linear combination of past values of the variable in study, and a moving averages component of order q, which includes a regression on the past errors. Additionally, the Box-Jenkins methodology implies that a transformation - differencing, relating to the parameter d - is applied to said combination with the purpose of stabilizing the mean of the time series in study by eliminating any changes in the time trend, whether it's deterministic or stochastic. This transformation makes sense when we are trying to fit a model to data that is not stationary, meaning the time series has a unit root (Box and Jenkins 1970). Hence, we can perform unit root testing to assess if a time series is stationary or if it has a unit root that needs to be removed, with the objective of determining whether differencing the series is required. For example, KPSS tests start with a potential random walk to assess which hypothesis is more likely - $H_0: \sigma_\epsilon^2 = 0$ vs. $H_1: \sigma_\epsilon^2 > 0$, as in the process is stationary vs. it isn't and has a unit root. Admittedly, considering we are studying two series that already have one difference applied to them, we expect the tests performed to give evidence on them being stationary. Starting with the GDP_{pc} for China, we can see in the ACF and PACF (Figure 48) plots a few spikes in lags 7 and 8 but they seem to not be relevant. The KPSS test performed confirms this expectation as it produces a statistic with a p-value above the 1% nominal size. With this result we don't reject H_0 and have evidence to assume that the series is stationary and does not need to be differenced once again. The same results are obtained for the other countries with this series - the software generated a p-value = 0.1 meaning that it is actually greater than 0.1. This allows us to once again not reject H_0 and have evidence to assume that the GDP_{pc} series for USA (Figure 49) and Kuwait (Figure 50) is in fact stationary. Equally, the KPSS tests performed for all the $CO_{2_{pc}}$ series calculate statistics with p-values above the nominal size and we have guaranteed evidence that we are working with series that do not need to be differenced (Figures 51 to 53). It should be noted that, when estimating an ARIMA model we can apply the same assumptions of stationarity and invertibility has done for AR and MA models, respectively. For the case of ARIMA models and similarly to exponential smoothing models, we are estimating the parameters using maximum likelihood estimation, which finds the fitted values that maximize the probability of the model returning the data that has already been observed.

Likewise, we also get the same parameter estimates as we would with LS estimation on linear regression models if the same assumptions are verified. With this in mind, we continue to follow the Box-Jenkins methodology to try to fit a model to the differenced series in study. The GDP_{pc} series for China's PACF plot suggests an AR(3) model and the ACF plot a MA(3) model, so we have two candidate models for the series - ARIMA(3,1,0) and ARIMA(0,1,3). Fitting both model options along with two automated model selections methods gives us identical AICc values (Figure 54). Nevertheless, the stepwise automated search method has found that the ARIMA(2,0,3) model has produced the lowest AICc score. The estimation produced for this model also shows that the resulting residuals are within the threshold limits, indicating that these are not serially correlated (Figure 55). This supposition is confirmed by the Ljung-Box test performed, which returns a p-value = 0.356. We conclude that the ARIMA(2,0,3) model is the best to forecast the differenced series of GDP_{pc} for China. For the remaining series in analysis in this MFW we obtained some interesting results. The differenced GDP_{pc} series for the USA is best fitted by an ARIMA(0,0,1) (Figure 56), as well as both $CO_{2_{pc}}$ for China and the USA (Figures 59 and 60). In addition, at a 1% nominal size, all the autocorrelation tests performed on these models residuals allow us to not reject the H_0 of no serial correlation on the errors and to evaluate the fitted models estimated as acceptable for these series. In contrast, for Kuwait's and Qatar's series for GDP_{pc} and $CO_{2_{pc}}$ respectively (Figures 57 and 58), the selected model is an ARIMA(0,0,0). The portmanteau tests performed further confirm this selection, with large p-values calculated that give us evidence that the residuals are white noise.

4. FORECASTING

After fitting a few models into our data, we should now check whether these models will perform good quality forecasting. If we think of forecasts as a random variable, we can say that prediction intervals mark the range of values in which the actual future values will fall in, with a certain percentage of probability. The average of these possible future values is called point forecast. With that being said, we can measure the uncertainty on a model's forecasts with a probability distribution associated to them, whose mean is the point forecasts. Thus, assessing a model's forecast will then be associated with the standard deviation of the forecast distribution. Usually, the further in time we are forecasting, the more uncertainty there is associated with these forecasts and thus the bigger will be the prediction intervals calculated. Hence, the standard deviation of the forecast distribution increases with the number of observations we are forecasting, h. For the most part, the accuracy of a models forecasts can be assessed the best on new data that was not used to fit the data in study. For this reason, we usually require training data to estimate the models and test data to evaluate their accuracy, by averaging a few accuracy measures over the test sets used. With time series cross-validation, these test sets assume only one observation and the corresponding training sets the observations prior to that one. Additionally, this procedure also allows for multi-step forecast errors to be calculated. In order to assess the accuracy of a forecast based on its errors, $e_{T+h} = y_{T+h} - \hat{y}_{T+h|T}$, we can use two commonly used measures: the Mean absolute error - $\text{MAE} = \text{mean}(|e_t|)$ - which minimized will lead to forecast of the median; or the Root mean squared error - $\text{RMSE} = \sqrt{\text{mean}(e_t^2)}$ - which leads to forecasts of the mean. Examining these measures calculated for the models on the GDP_{pc} series for China (Figure 61), we see that the ARIMA(2,0,3) produces both the lowest MAE and RMSE, meaning that this model is the best out of the selected to forecast this series. We can also see that these measures calculated are very close to the ones for the ETS model. This result is expected as linear ETS models are a particular case of ARIMA models. Regardless, we can only choose between these models using forecast accuracy measurements and not information criteria, as their likelihood is computed differently. The forecast values estimated indicate that the Chinese GDP_{pc} will likely continue to grow over the next years, following a very similar trajectory has the one recorded since the 1980s. It is estimated that there's an 80% chance that this growth will vary throughout the years between -5% and 12%. For this same series for the USA we select the ETS model when comparing accuracy measurements calculated for all models previously estimated (Figure 62), due to the low MAE and RMSE values produced. The $\text{ETS}(\text{A}, \text{N}, \text{N})$ model forecasts that the GDP_{pc} indicator for the USA will likely stabilize and behave similarly to what has been registered in the last 50 years, balancing between periods of growth and decline. It is estimated that there's an 80% chance that the GDP_{pc} will vary between -4% and 11% yearly. As for the data on Kuwait, the model that most accurately fits the GDP_{pc} growth rate series is the $\text{ARIMA}(0,0,0)$ (Figure 63). Since this model represents a cumulative sum of shocks, all predictions calculated are constant. As for the $CO_{2_{pc}}$ growth rate series, Qatar produces the smallest prediction error with the ARIMA(0,0,0) as well (Figure 64). As a result, the forecasted future values of the series are also constant. Following with China, analysing the RMSE calculations we see that the $CO_{2_{pc}}$ growth rate seems to be best forecasted also by the ARIMA model, particularly the ARIMA(0,0,1) already estimated (Figure 65). As such and for the most part, it's previsions indicate that the $CO_{2_{pc}}$ for the country will most likely continue to grow as opposed to decrease. Particularly, the series should follow a trajectory similar to the one registered since 1975, with some variability and a likelihood of varying between -15% and 15% of 80%. Last but not least, the accuracy testing methodology applied to the American series indicates that the ARIMA(0,0,1) also produces the best forecasts for this series (Figure 66). This model estimates that this series will likely have zero mean and follow a steadier variation pattern, with a likelihood of 80% of changing between -4% and 4% throughout the next decades.

5. CONCLUSION

Most forecasts produced above seem to mimic very precisely these series' past recent behaviour, making it easy to believe that these are accurate and usable for policy management. Nonetheless, the prediction intervals produced are in almost all cases very wide and should be evaluated with caution. Additionally, the probability of decreasing GDP_{pc} or increasing $CO_{2_{pc}}$ is too prominent to not use all political instruments available to manage these indicators' evolution in the next few decades. To particularize, China's chance of a continuous growing $CO_{2_{pc}}$ will, without a doubt, negatively impact the quality of our environment. Considering this country is the number one economy in global carbon emissions, accounting for about 27% of them in 2019, a realisation of the worst-case scenario predicted can imply an increase in global annual CO_2 emissions of about 400 thousand metric tons of carbon. Furthermore, considering the results obtained, it is very difficult to verify if the principles of the environmental Kuznets curve are applicable nowadays and to most economies. As mentioned before, if these principles were true, we would likely have forecasted a decreasing trend in $CO_{2_{pc}}$ growth rate for countries with high GDP_{pc} levels such as the USA, which was not confirmed. More studying is required over a bigger group of countries to detail if this relationship between growth and environment degradation is more present in economies with different characteristics.

The fact that for most series the best model to perform its forecasts with was the ARIMA, may indicate that this study would benefit from using models that include more information relevant to the series. Not only is it important to include in a model lagged variables but also the effects of past changes, as it does not make sense to assume that the data observed belongs in an economy at equilibrium. The best way to do so might be, that in each period the economy is not only adjusting from shocks from the past but also to new ones that push it away from the equilibrium. It is with this premise that dynamic models might become more appropriate to study non-contemporary relationships between variables. One can wonder whether a dramatic increase in GDP_{pc} in one year, derived from a big investment in the exploration of a coal mine, can have an impact in CO_2 emissions in the years following, for example. Or the contrary, whether a steady yearly increase in CO_2 emissions in a territory with a massive drought as a direct consequence, might eradicate important crops that compose the majority of the countries' exports, therefore impacting the GDP_{pc} negatively. This also raises the question of whether variables can affect each other simultaneously, as oppose to the unidirectional relationship that is usually considered. These feedback relationships can be modelled with vector autoregressive models (VAR), where all estimated variables are endogenous, and forecasting is done on a vector of time series.

All in all, as time goes by it becomes increasingly important to continue the study on the social and economic impacts of climate change on human lives, to assist in worldwide efforts on building a more sustainable and just world.

REFERENCES

Box, G.E.P. & Jenkins, G.M. (1970). "Time Series Analysis: Forecasting and Control". *San Francisco: Holden-Day.*

DARA and the Climate Vulnerable Forum (2010). "Climate Vulnerability Monitor 2010 - The State of the Climate Crisis". Available from: https://daraint.org/climate-vulnerability-monitor/climate-vulnerability-monitor-2010/

Grossman, G. M., & Krueger, A. B. (1991). "Environmental impacts of a North American free trade agreement". *National Bureau of Economic Research Working Paper Series*, 3914.

Grossman, G. M. & Krueger, A. B. (1995). "Economic Growth and the Environment". *Quarterly Journal of Economics*, 110, 353-377.

Hayashi, F. (2000). "Econometrics". *Cambridge University Press.*

Hyndman, R.J. & Athanasopoulos, G. (2021). "Forecasting: principles and practice, 3rd edition". *OTexts*. Available from: OTexts.com/fpp3

IEA (2021). "Global Energy Review: CO2 Emissions in 2020". Available from: https://www.iea.org/articles/global-energy-review-co2-emissions-in-2020

IPCC (2021). "Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change". *Cambridge University Press*. Available from: https://www.ipcc.ch/report/ar6/wg1/#FullReport

Li, T., Wang, Y. & Zhao, D. (2016). "Environmental Kuznets curve in China: New evidence from dynamic panel analysis". *Energy Policy*, 91, 138–147.

Ozturk, I. & Al-Mulali, U. (2015). "Investigating the validity of the environmental Kuznets curve hypothesis in Cambodia". *Ecological Indicators,* 57, 324–330.

Shikwambana, L., Mhangara, P. & Kganyago, M. (2021). " Assessing the Relationship between Economic Growth and Emissions Levels in South Africa between 1994 and 2019". *Sustainability*, 13, 2645.

Stern, D. I. & Common, M. S. (2001). "Is there an environmental Kuznets curve for sulfur?". *Journal of Environmental Economics and Management*, 41, 162-178.

Ster, D. I. & Perman, R. (2003). " Evidence from panel unit root and cointegration tests that the Environmental Kuznets Curve does not exist". *The Australian Journal of Agricultural and Resource Economics*, 47:3, 325–347.

Wei, W. (1989). "Time Series Analysis: Univariate and Multivariate Methods". *Allan M. Wylde.*

Wooldridge, J.M. (2013). "Introductory Econometrics". *South-Western,* 5.

APPENDICES

Figure 1 - $\Delta\log(GDP_{pc})$ descending mean ranking

\# A tibble: 169 x 2

	country	mean
	<chr>	<dbl>
1	Kuwait	0.0430
2	Malta	0.0428
3	Libya	0.0422
4	Saudi Arabia	0.0372
5	Cabo Verde	0.0341
6	Romania	0.0309
7	Norway	0.0276
8	Mauritius	0.0255
9	Japan	0.0246
10	Saint Lucia	0.0245

\# ... with 159 more rows

Figure 2 - $\Delta\log(GDP_{pc})$ ascending mean ranking

\# A tibble: 169 x 2

	country	mean
	<chr>	<dbl>
1	Central African Republic	-0.0620
2	Madagascar	-0.0535
3	Senegal	-0.0428
4	Benin	-0.0418
5	Syrian Arab Republic	-0.0415
6	Sierra Leone	-0.0415
7	Ethiopia	-0.0392
8	Mali	-0.0391
9	Djibouti	-0.0383
10	Rwanda	-0.0369

\# ... with 159 more rows

Figure 3 - $\Delta\log(GDP_{pc})$ quantiles ranking, descending from the maximum

\# A tibble: 169 x 6

	country	`0%`	`25%`	`50%`	`75%`	`100%`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	Kuwait	-0.436	-0.0502	0.000597	0.0570	2.61
2	Saudi Arabia	-1.36	0.00409	0.0455	0.0779	1.31
3	Côte d'Ivoire	-3.21	-0.0153	0.0142	0.0442	1.03
4	Romania	-0.387	-0.00622	0.0340	0.0792	1.01
5	Libya	-0.816	-0.00739	0.0566	0.127	0.837
6	Iran (Islamic Republic of)	-2.23	-0.0211	0.0490	0.0784	0.766
7	Morocco	-2.85	0.00286	0.0193	0.0341	0.717
8	Equatorial Guinea	-2.38	-0.0188	0.0290	0.0996	0.646
9	Syrian Arab Republic	-3.39	-0.0577	-0.00975	0.0474	0.616
10	Lebanon	-2.35	-0.00914	0.0369	0.0896	0.593

\# ... with 159 more rows

Figure 4 - $\Delta\log(GDP_{pc})$ quantiles ranking from 1931 to 1940, descending from the maximum

\# A tibble: 68 x 6

	country	`0%`	`25%`	`50%`	`75%`	`100%`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	Guatemala	-0.160	-3.70e-2	0.0539	0.109	0.297
2	Nicaragua	-0.255	-9.97e-2	0.00452	0.0624	0.215
3	Chile	-0.280	-1.52e-4	0.0149	0.0913	0.204
4	Republic of Korea	-0.183	-2.94e-2	0.00554	0.0429	0.204
5	Venezuela (Bolivarian Republic ~	-0.0972	5.99e-3	0.0530	0.0934	0.174
6	New Zealand	-0.103	-1.89e-2	0.0402	0.0529	0.163
7	Turkey	-0.0797	5.34e-3	0.0289	0.0629	0.157
8	Costa Rica	-0.144	-5.10e-2	0.0178	0.0571	0.155
9	D.P.R. of Korea	-0.0556	1.02e-2	0.0427	0.0607	0.152
10	Portugal	-0.0913	-5.16e-2	0.00418	0.0356	0.143

\# ... with 58 more rows

Figure 5 - $\Delta\log(GDP_{pc})$ quantiles ranking from 2011 to 2018, descending from the maximum

\# A tibble: 169 x 6

	country	`0%`	`25%`	`50%`	`75%`	`100%`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	Libya	-0.816	-4.36e-1	-0.0922	0.226	0.837
2	Mongolia	-0.00307	2.67e-2	0.0545	0.0969	0.192
3	Chad	-0.0853	-4.07e-2	0.0177	0.0578	0.188
4	Sierra Leone	-0.250	1.97e-2	0.0295	0.0595	0.166
5	Venezuela (Bolivarian Republ~	-0.211	-1.71e-1	-0.0654	0.0386	0.144
6	Qatar	-0.0105	-7.00e-3	0.00163	0.00596	0.143
7	Turkmenistan	0.0486	5.05e-2	0.0684	0.0886	0.137
8	Saudi Arabia	-0.0275	6.95e-4	0.00985	0.0216	0.126
9	Paraguay	-0.0253	2.29e-2	0.0307	0.0346	0.119
10	Kuwait	-0.0730	-3.94e-2	-0.0117	0.00175	0.113

\# ... with 159 more rows

Figure 6 - Plot of $\Delta\log(GDP_{pc})$ for China

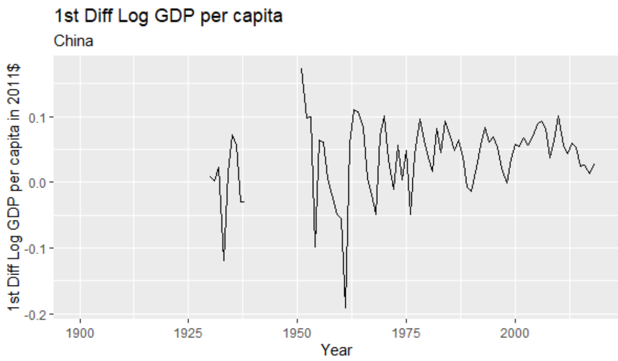


Figure 7 - Mean of $\Delta\log(GDP_{pc})$ for China

```
# A tibble: 1 x 2
  country    ...1
  <chr>     <dbl>
1 China    0.0411
```

Figure 8 - Plot of $\Delta\log(GDP_{pc})$ for the USA

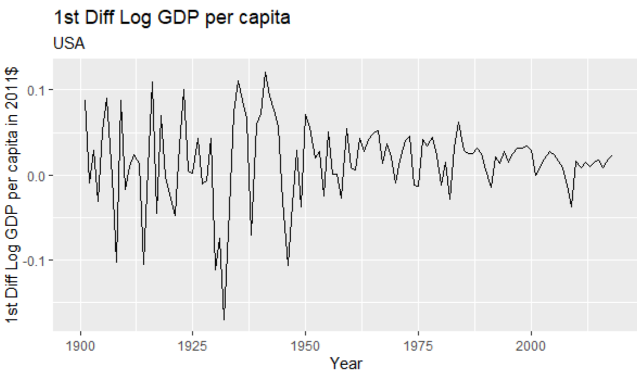


Figure 9 - Mean of $\Delta\log(GDP_{pc})$ for the USA

```
# A tibble: 1 x 2
  country            ...1
  <chr>             <dbl>
1 United States 0.0163
```

Figure 10 - Plot of $\Delta\log(GDP_{pc})$ for France, Germany, Italy, Russia, and UK

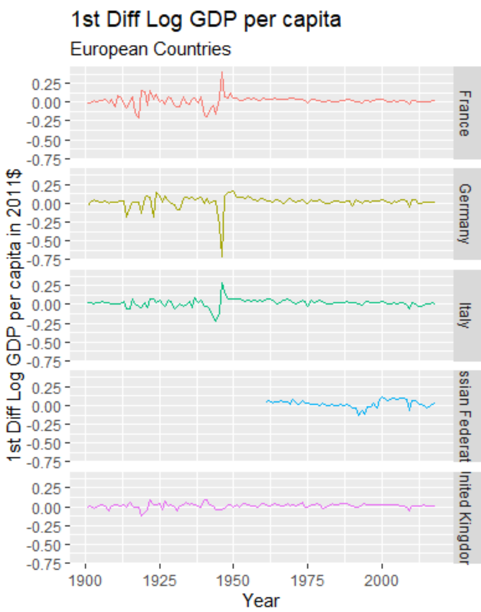


Figure 11 - Shift in $\Delta\log(GDP_{pc})$ USA series level

A tibble: 1 x 3

	country	shift_level_max	shift_level_index
	<chr>	<dbl>	<dbl>
1	United States	0.101	34

33	United States	1933	-0.0405
34	United States	1934	0.0741
35	United States	1935	0.111

Figure 12 - 2008 value of $\Delta\log(GDP_{pc})$ USA series

107	United States	2007	0.00812
108	United States	2008	-0.0124
109	United States	2009	-0.0369

Figure 13 - Plot of $\Delta\log(GDP_{pc})$ for Kuwait

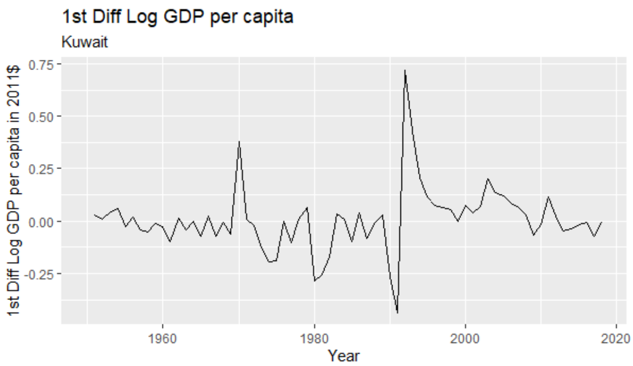


Figure 14 - Values of $\Delta\log(GDP_{pc})$ for Kuwait

20	Kuwait	1969	-0.0618
21	Kuwait	1970	0.381
22	Kuwait	1971	0.00764

42	Kuwait	1991	-0.436
43	Kuwait	1992	0.720
44	Kuwait	1993	0.431

Figure 15 - $\Delta\log(GDP_{pc})$ descending mean ranking for 8 regions

A tibble: 8 x 2

	region	mean
	<chr>	<dbl>
1	Asia (East)	0.248
2	Middle East	0.215
3	Eastern Europe	0.186
4	Asia (South and South-East)	0.182
5	Western Europe	0.171
6	Latin America	0.154
7	Western Offshoots	0.153
8	Sub-Sahara Africa	0.117

Figure 16 - $\Delta\log(GDP_{pc})$ quantiles ranking for 8 regions, descending from the maximum

A tibble: 8 x 6

	region	\`0%\`	\`25%\`	\`50%\`	\`75%\`	\`100%\`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	Eastern Europe	-0.141	0.0355	0.160	0.321	0.639
2	Asia (East)	-0.193	0.0672	0.307	0.421	0.561
3	Middle East	-0.0465	0.0348	0.185	0.388	0.551
4	Sub-Sahara Africa	-0.118	0.0156	0.0983	0.182	0.465
5	Asia (South and South-East)	-0.144	0.0787	0.198	0.283	0.446
6	Western Europe	0.0109	0.0222	0.166	0.256	0.413
7	Latin America	-0.0707	0.0114	0.217	0.267	0.328
8	Western Offshoots	0.0178	0.0742	0.190	0.218	0.284

Figure 17 - $\Delta\log(CO_{2pc})$ descending mean ranking

A tibble: 255 x 2

	country	mean
	<chr>	<dbl>
1	CURACAO	0.443
2	SAINT MARTIN (DUTCH PORTION)	0.372
3	SERBIA	0.176
4	FRENCH INDO-CHINA	0.173
5	ESTONIA	0.157
6	UKRAINE	0.130
7	MALAYSIA	0.0977
8	PALAU	0.0936
9	LEEWARD ISLANDS	0.0933
10	GEORGIA	0.0869

... with 245 more rows

Figure 18 - Means for $\Delta\log(CO_{2pc})$

25	FRENCH POLYNESIA	0.0573
26	CHINA (MAINLAND)	0.0573
27	LESOTHO	0.0554
64	SAUDI ARABIA	0.0351
65	CAYMAN ISLANDS	0.0347
66	KUWAIT	0.0347
160	SWEDEN	-0.000405
161	UNITED STATES OF AMERICA	-0.000675
162	BELGIUM	-0.000893
165	LUXEMBOURG	-0.00742
166	UNITED KINGDOM	-0.00882
167	SAO TOME & PRINCIPE	-0.0112

Figure 19 - $\Delta\log(CO_{2pc})$ quantiles ranking, descending from the maximum

A tibble: 255 x 6

	country	\`0%\`	\`25%\`	\`50%\`	\`75%\`	\`100%\`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	UKRAINE	-0.196	-0.0760	-0.0263	0.0154	4.42
2	ESTONIA	-0.180	-0.0645	-0.00960	0.0560	4.27
3	UNITED ARAB EMIRATES	-3.68	-0.0933	-0.0355	0.0542	3.60
4	Qatar	-0.782	-0.115	-0.0234	0.0609	3.38
5	KUWAIT	-2.21	-0.106	0.00568	0.115	3.31
6	MALAYSIA	-0.121	-0.0144	0.0385	0.0826	2.92
7	CURACAO	-0.161	-0.132	0.00588	0.101	2.86
8	BRUNEI (DARUSSALAM)	-1.57	-0.122	-0.0166	0.0729	2.78
9	GEORGIA	-0.932	-0.0744	0.0646	0.146	2.42
10	ISLAMIC REPUBLIC OF IRAN	-1.10	-0.00723	0.0300	0.0818	2.40

... with 245 more rows

Figure 20 - Δlog ($CO_{2_{pc}}$) quantiles ranking from 1961 to 1970, descending from the maximum

A tibble: 194 x 6

	country	`0%`	`25%`	`50%`	`75%`	`100%`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	CHAD	-Inf	0	0	0	Inf
2	SWAZILAND	-Inf	0.113	0.156	1.08	Inf
3	UNITED ARAB EMIRATES	-0.441	0	0.112	0.275	3.60
4	Qatar	-0.161	-0.0795	-0.0476	-0.0158	3.38
5	MALAYSIA	2.92	2.92	2.92	2.92	2.92
6	BRUNEI (DARUSSALAM)	-0.165	-0.0830	-0.0668	0.127	2.78
7	LIBYAN ARAB JAMAHIRIYAH	-0.821	-0.0731	0.352	0.506	1.91
8	SEYCHELLES	-3.56	-0.0719	0	0	1.67
9	BRITISH VIRGIN ISLANDS	-1.86	-0.0194	0	0.642	1.59
10	SINGAPORE	-1.31	0.0827	0.267	0.505	1.46

... with 184 more rows

Figure 21 - Δlog ($CO_{2_{pc}}$) quantiles ranking from 1971 to 1980, descending from the maximum

A tibble: 188 x 6

	country	`0%`	`25%`	`50%`	`75%`	`100%`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	BURUNDI	0	0	0	0	Inf
2	NEPAL	-Inf	0	0	0	Inf
3	OMAN	-0.300	-0.0590	-0.0305	0.0842	2.13
4	TOGO	-0.693	-0.167	0	0.167	1.25
5	GREENLAND	-0.844	-0.0814	-0.00803	0.178	1.19
6	BOTSWANA	-5.18	0	0.251	0.693	1.10
7	CAPE VERDE	-0.693	0.0334	0.134	0.175	0.965
8	MONTSERRAT	-0.460	-0.162	0	0	0.952
9	BAHAMAS	-0.407	-0.0777	0.0574	0.160	0.934
10	FRENCH GUIANA	-0.416	-0.0493	0.0258	0.166	0.809

... with 178 more rows

Figure 22 - Δlog ($CO_{2_{pc}}$) quantiles ranking from 2001 to 2010, descending from the maximum

A tibble: 222 x 6

	country	`0%`	`25%`	`50%`	`75%`	`100%`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	SERBIA	-0.138	-0.116	-0.0167	0	2.37
2	EQUATORIAL GUINEA	-0.258	-0.0741	0.00487	0.148	2.23
3	NIUE	-0.683	0	0.0200	0.0215	0.703
4	AFGHANISTAN	0	0	0	0.376	0.693
5	VANUATU	-0.318	-0.0853	0	0	0.693
6	ETHIOPIA	0	0	0	0	0.693
7	NIGER	-0.693	0	0	0	0.693
8	SOMALIA	-0.693	0	0	0	0.693
9	TUVALU	-0.693	-0.249	0	0.216	0.663
10	ANGOLA	-0.357	0	0.0303	0.103	0.657

... with 212 more rows

Figure 23 - Δlog ($CO_{2_{pc}}$) quantiles ranking from 2011 to 2017, descending from the maximum

A tibble: 219 x 6

	country	`0%`	`25%`	`50%`	`75%`	`100%`
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	CURACAO	-0.161	-0.132	0.00588	0.101	2.86
2	SAINT MARTIN (DUTCH PORTION)	-0.0318	-0.00914	-0.00777	-0.00193	2.29
3	MOZAMBIQUE	-0.405	-0.144	0.288	0.288	0.811
4	LAO PEOPLE S DEMOCRATIC REPUB~	0	0.0716	0.182	0.326	0.747
5	CHAD	-0.693	-0.347	0	0.347	0.693
6	DEMOCRATIC REPUBLIC OF THE CO~	-0.693	0	0	0	0.693
7	NIUE	-0.405	0	0	0.208	0.683
8	MONGOLIA	-0.410	-0.0963	0.200	0.354	0.471
9	TIMOR-LESTE (FORMERLY EAST TI~	-0.0870	0	0	0.121	0.452
10	SINGAPORE	-0.651	-0.241	0.00367	0.104	0.445

... with 209 more rows

Figure 24 - Plot of Δlog ($CO_{2_{pc}}$) for Qatar

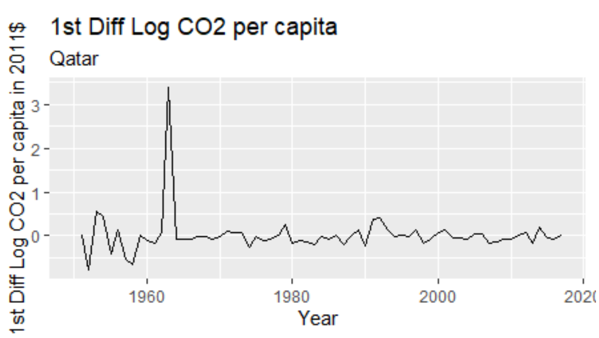


Figure 25 - Mean of Δlog ($CO_{2_{pc}}$) for Qatar

A tibble: 1 x 2

	country	...1
	<chr>	<dbl>
1	Qatar	0.0151

Figure 26 - Plot of $\Delta\log(CO_{2_{pc}})$ for Russia

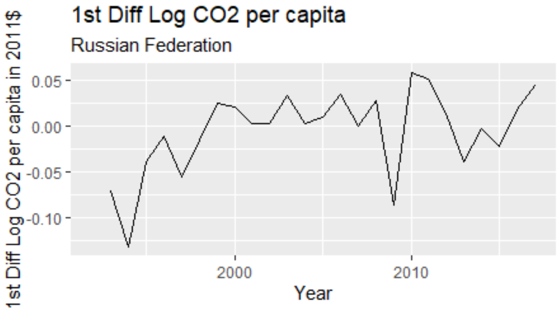


Figure 27 - Mean of $\Delta\log(CO_{2_{pc}})$ for Russia

```
# A tibble: 1 x 2
  country                ...1
  <chr>                 <dbl>
1 RUSSIAN FEDERATION -0.00478
```

Figure 28 - Plot of $\Delta\log(CO_{2_{pc}})$ for Sweden

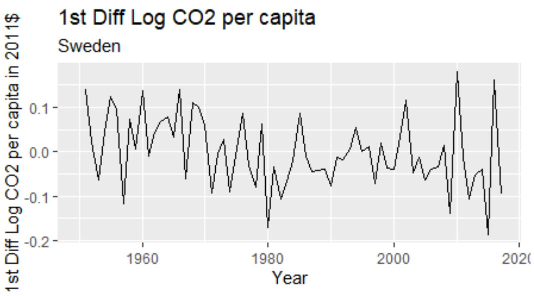


Figure 29 - Mean of $\Delta\log(CO_{2_{pc}})$ for Sweden

```
# A tibble: 1 x 2
  country       ...1
  <chr>        <dbl>
1 SWEDEN  -0.000405
```

Figure 30 - Estimation of $(1-B)\log(GDP_{pc}) = \beta_0 + \beta_1 trend + u_t$ for China

```
Series: gdppc
Model: TSLM

Residuals:
      Min        1Q    Median        3Q       Max
-0.215665 -0.029555  0.005921  0.031627  0.153667

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0044383  0.0177571  -0.250   0.8033
trend()      0.0006121  0.0002501   2.447   0.0167 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05395 on 75 degrees of freedom
Multiple R-squared: 0.07394,    Adjusted R-squared: 0.06159
F-statistic: 5.988 on 1 and 75 DF, p-value: 0.016743
```

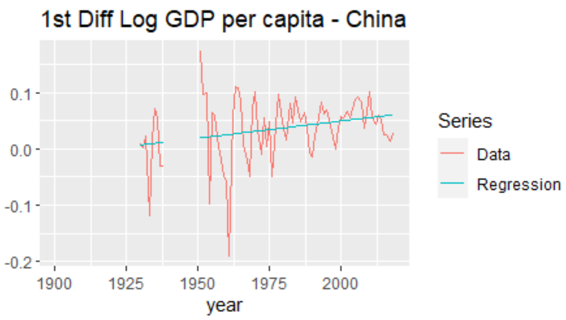


Figure 31 - Estimation of $(1-B)\log(GDP_{pc}) = \beta_0 + \beta_1 trend + u_t$ for USA

```
Series: gdppc
Model: TSLM

Residuals:
      Min        1Q    Median        3Q       Max
-0.184716 -0.018135  0.002095  0.025498  0.105887

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.396e-02  7.424e-03   1.881   0.0625 .
trend()     5.028e-05  1.270e-04   0.396   0.6929
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04699 on 116 degrees of freedom
Multiple R-squared: 0.001349,    Adjusted R-squared: -0.00726
F-statistic: 0.1568 on 1 and 116 DF, p-value: 0.69289
```

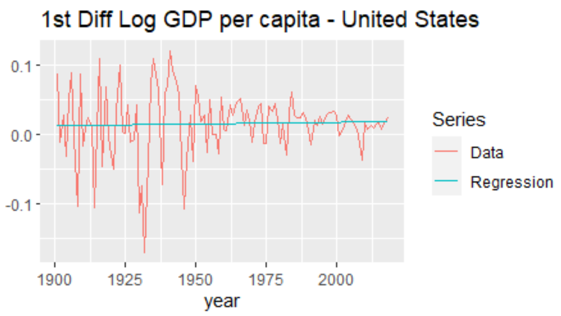


Figure 32 - Estimation of $(1-B)\log(GDP_{pc}) = \beta_0 + \beta_1 trend + u_t$ for Kuwait

```
Series: gdppc
Model: TSLM

Residuals:
     Min       1Q   Median       3Q      Max
-0.46373 -0.13081 -0.04837  0.03832  2.49659

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.196774   0.158097   1.245    0.218
trend()     -0.002136   0.002116  -1.009    0.316

Residual standard error: 0.3501 on 67 degrees of freedom
Multiple R-squared: 0.01498,    Adjusted R-squared: 0.0002762
F-statistic: 1.019 on 1 and 67 DF, p-value: 0.31644
```

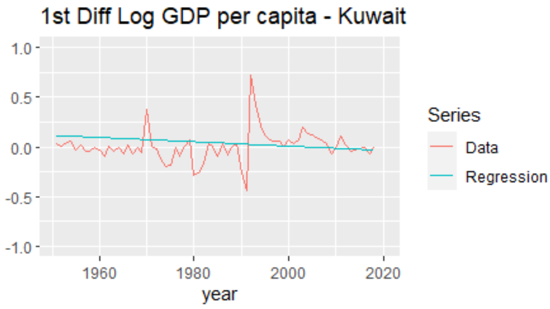
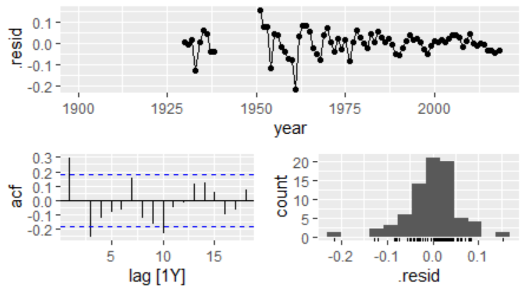
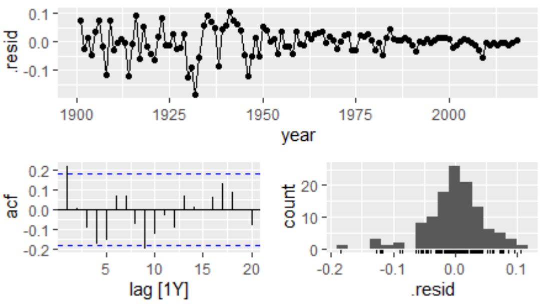


Figure 33 - Histogram, ACF plot and Ljung-Box test results for the residuals of regression for China



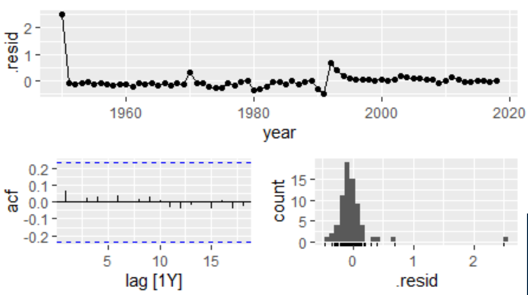

```
# A tibble: 1 x 4
  country .model      lb_stat lb_pvalue
  <chr>   <chr>         <dbl>     <dbl>
1 China   trend_model    23.7   0.00129
```

Figure 34 - Histogram, ACF plot and Ljung-Box test results for the residuals of regression for USA




```
# A tibble: 1 x 4
  country       .model      lb_stat lb_pvalue
  <chr>         <chr>         <dbl>     <dbl>
1 United States trend_model    22.9  0.000359
```

Figure 35 - Histogram, ACF plot and Ljung-Box test results for the residuals of regression for Kuwait




```
# A tibble: 1 x 4
  country .model      lb_stat lb_pvalue
  <chr>   <chr>         <dbl>     <dbl>
1 Kuwait  trend_model   0.698     0.983
```

Figure 36 - Estimation of $(1-B)\log\left(CO_{2_{pc}}\right) = \beta_0 + \beta_1 trend + u_t$ for Qatar

```
Series: CO2pc
Model: TSLM

Residuals:
     Min       1Q   Median       3Q      Max
-0.83588 -0.13159 -0.04725  0.04429  3.34329

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.056008   0.116626   0.480    0.633
trend()     -0.001204   0.002982  -0.404    0.688

Residual standard error: 0.472 on 65 degrees of freedom
Multiple R-squared: 0.0025,     Adjusted R-squared: -0.01285
F-statistic: 0.1629 on 1 and 65 DF, p-value: 0.68779
```

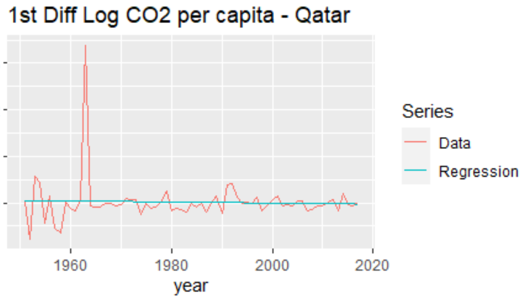


Figure 37 - Estimation of $(1-B)\log\left(CO_{2_{pc}}\right) = \beta_0 + \beta_1 trend + u_t$ for China

```
Series: CO2pc
Model: TSLM

Residuals:
     Min       1Q   Median       3Q      Max
-0.45987 -0.03739 -0.01169  0.03917  0.60433

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0985125  0.0314968   3.128  0.00264 **
trend()     -0.0012120  0.0008052  -1.505  0.13713
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1275 on 65 degrees of freedom
Multiple R-squared: 0.03368,    Adjusted R-squared: 0.01881
F-statistic: 2.265 on 1 and 65 DF, p-value: 0.13713
```

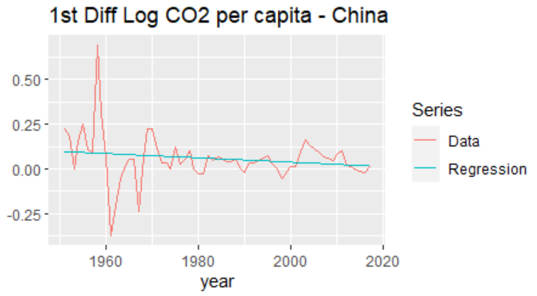


Figure 38 - Estimation of $(1-B)\log\left(CO_{2_{pc}}\right) = \beta_0 + \beta_1 trend + u_t$ for USA

```
Series: CO2pc
Model: TSLM

Residuals:
      Min        1Q    Median        3Q       Max
-0.077749 -0.015920  0.004885  0.020652  0.063994

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0134536  0.0075718   1.777   0.0803 .
trend()     -0.0004155  0.0001936  -2.147   0.0356 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03064 on 65 degrees of freedom
Multiple R-squared: 0.0662,     Adjusted R-squared: 0.05183
F-statistic: 4.608 on 1 and 65 DF, p-value: 0.035562
```

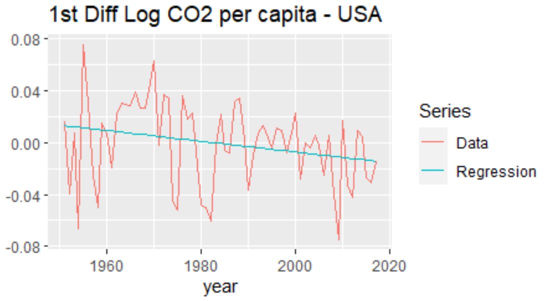
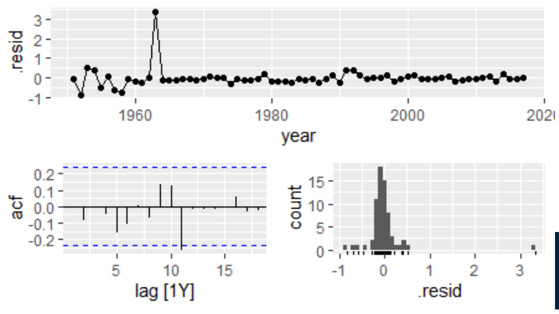
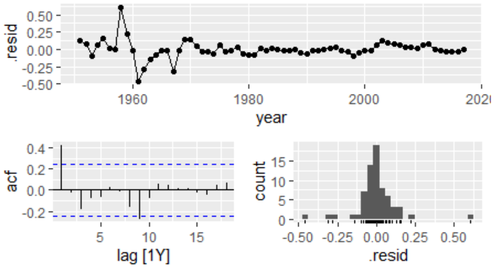


Figure 39 - Histogram, ACF plot and Ljung-Box test results for the residuals of regression for Qatar



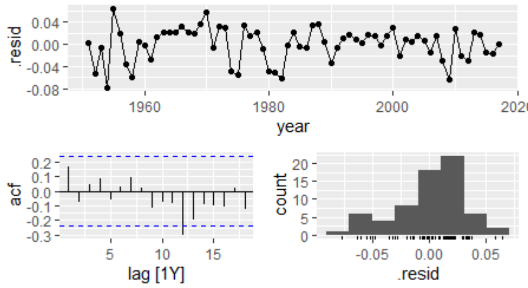

```
# A tibble: 1 x 4
  country .model      lb_stat lb_pvalue
  <chr>   <chr>         <dbl>     <dbl>
1 Qatar   trend_model    6.50     0.261
```

Figure 40 - Histogram, ACF plot and Ljung-Box test results for the residuals of regression for China




```
# A tibble: 1 x 4
  country           .model      lb_stat lb_pvalue
  <chr>             <chr>         <dbl>     <dbl>
1 CHINA (MAINLAND) trend_model     23.8  0.000232
```

Figure 41 - Histogram, ACF plot and Ljung-Box test results for the residuals of regression for USA




```
# A tibble: 1 x 4
  country                     .model      lb_stat lb_pvalue
  <chr>                       <chr>         <dbl>     <dbl>
1 UNITED STATES OF AMERICA trend_model     5.77     0.329
```

Figure 42 - China's $(1-B)\log(GDP_{pc})$ ETS models and information criteria scores

```
# A mable: 3 x 3
# Key:     country, Model name [3]
  country `Model name`       `Model type`
  <chr>   <chr>                   <model>
1 China   additive           <ETS(A,A,N)>
2 China   additive_damped   <ETS(A,Ad,N)>
3 China   additive_notrend   <ETS(A,N,N)>
```

```
# A tibble: 3 x 6
  .model            sigma2 log_lik   AIC  AICc   BIC
  <chr>              <dbl>   <dbl> <dbl> <dbl> <dbl>
1 additive_notrend 0.00299    55.2 -104.  -104.  -97.7
2 additive_damped  0.00320    54.4 -98.9  -97.9 -87.8
3 additive         0.00329    53.0 -96.0  -95.0 -84.9
```

```
Series: gdppc
Model: ETS(A,N,N)
  Smoothing parameters:
    alpha = 0.0001000122

  Initial states:
          l
 0.04113606

  sigma^2:  0.003

       AIC        AICc         BIC
-104.35368 -103.97868   -97.69515
```

Figure 43 - USA's $(1-B)\log(GDP_{pc})$ ETS models and information criteria scores

```
# A mable: 3 x 3
# Key:     country, Model name [3]
  country       `Model name`       `Model type`
  <chr>         <chr>                   <model>
1 United States additive           <ETS(A,A,N)>
2 United States additive_damped   <ETS(A,Ad,N)>
3 United States additive_notrend   <ETS(A,N,N)>
```

```
# A tibble: 3 x 6
  .model            sigma2 log_lik   AIC  AICc   BIC
  <chr>              <dbl>   <dbl> <dbl> <dbl> <dbl>
1 additive_notrend 0.00221    80.3 -155. -154. -146.
2 additive         0.00226    80.0 -150. -149. -136.
3 additive_damped  0.00229    79.9 -150. -149. -136.
```

```
Series: gdppc
Model: ETS(A,N,N)
  Smoothing parameters:
    alpha = 0.0001000021

  Initial states:
          l
 0.01635007

  sigma^2:  0.0022

      AIC      AICc       BIC
-154.5286 -154.3181 -146.2165
```

Figure 44 - Kuwait's $(1-B)\log(GDP_{pc})$ ETS models and information criteria scores

```
# A mable: 3 x 3
# Key:     country, Model name [3]
  country `Model name`       `Model type`
  <chr>   <chr>                   <model>
1 Kuwait  additive           <ETS(A,A,N)>
2 Kuwait  additive_damped   <ETS(A,Ad,N)>
3 Kuwait  additive_notrend   <ETS(A,N,N)>
```

```
# A tibble: 3 x 6
  .model           sigma2 log_lik   AIC  AICc   BIC
  <chr>             <dbl>   <dbl> <dbl> <dbl> <dbl>
1 additive_damped  0.0912   -60.9  132.  133.  143.
2 additive_notrend 0.126    -73.7  153.  154.  160.
3 additive         0.129    -73.2  156.  157.  168.
```

```
Series: gdppc
Model: ETS(A,Ad,N)
  Smoothing parameters:
    alpha = 0.02737929
    beta  = 0.01404549
    phi   = 0.8000012

  Initial states:
        l          b
 1.212419 -0.3530681

  sigma^2:  0.0921

     AIC     AICc      BIC
134.3854 135.7403 147.7901
```

Figure 45 - Qatar's $(1-B)\log\left(CO_{2_{pc}}\right)$ ETS models and information criteria scores

```
# A mable: 3 x 3
# Key:     country, Model name [3]
  country `Model name`       `Model type`
  <chr>   <chr>                   <model>
1 Qatar   additive            <ETS(A,A,N)>
2 Qatar   additive_damped    <ETS(A,Ad,N)>
3 Qatar   additive_notrend    <ETS(A,N,N)>
```

```
# A tibble: 3 x 6
  .model           sigma2 log_lik   AIC  AICc   BIC
  <chr>             <dbl>   <dbl> <dbl> <dbl> <dbl>
1 additive_notrend 0.000999    91.6 -177. -177. -171.
2 additive         0.000974    93.5 -177. -176. -166.
3 additive_damped  0.00104     91.9 -174. -173. -163.
```

```
Series: co2pc
Model: ETS(A,N,N)
  Smoothing parameters:
    alpha = 0.0001000285

  Initial states:
          l
 0.01504893

  sigma^2:  0.2233

     AIC     AICc      BIC
185.2480 185.6289 191.8620
```

Figure 46 - China's $(1-B)\log\left(CO_{2_{pc}}\right)$ ETS models and information criteria scores

```
# A mable: 3 x 3
# Key:     country, Model name [3]
  country            `Model name`       `Model type`
  <chr>              <chr>                   <model>
1 CHINA (MAINLAND) additive            <ETS(A,A,N)>
2 CHINA (MAINLAND) additive_damped    <ETS(A,Ad,N)>
3 CHINA (MAINLAND) additive_notrend    <ETS(A,N,N)>
```

```
# A tibble: 3 x 6
  .model           sigma2 log_lik   AIC  AICc   BIC
  <chr>             <dbl>   <dbl> <dbl> <dbl> <dbl>
1 additive_damped  0.0161  0.0458  9.91  10.9  20.9
2 additive_notrend 0.0168 -2.98    12.0  12.3  18.6
3 additive         0.0170 -2.31    14.6  15.6  25.6
```

```
Series: co2pc
Model: ETS(A,Ad,N)
  Smoothing parameters:
    alpha = 0.0004493023
    beta  = 0.0001000001
    phi   = 0.8

  Initial states:
         l           b
 0.2891529 -0.06163393

  sigma^2:  0.0161

     AIC      AICc       BIC
9.908403 10.892010 20.931866
```

Figure 47 - USA's $(1-B)\log\left(CO_{2_{pc}}\right)$ ETS models and information criteria scores

```
# A mable: 3 x 3
# Key:     country, Model name [3]
  country                  `Model name`       `Model type`
  <chr>                    <chr>                   <model>
1 UNITED STATES OF AMERICA additive            <ETS(A,A,N)>
2 UNITED STATES OF AMERICA additive_damped    <ETS(A,Ad,N)>
3 UNITED STATES OF AMERICA additive_notrend    <ETS(A,N,N)>
```

```
# A tibble: 3 x 6
  .model           sigma2 log_lik   AIC  AICc   BIC
  <chr>             <dbl>   <dbl> <dbl> <dbl> <dbl>
1 additive_notrend 0.000999    91.6 -177. -177. -171.
2 additive         0.000974    93.5 -177. -176. -166.
3 additive_damped  0.00104     91.9 -174. -173. -163.
```

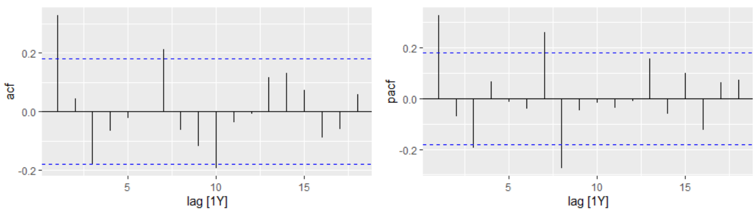
```
Series: co2pc
Model: ETS(A,N,N)
  Smoothing parameters:
    alpha = 0.08832052

  Initial states:
           l
 0.003462188

  sigma^2:  0.001

      AIC      AICc       BIC
-177.1809 -176.7999 -170.5668
```

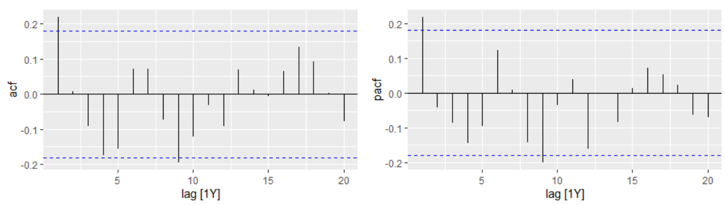
Figure 48 - China's $(1-B)\log(GDP_{pc})$ series ACF and PACF plots and KPSS test result




```
# A tibble: 1 x 3
  country kpss_stat kpss_pvalue
  <chr>       <dbl>       <dbl>
1 China       0.458      0.0521
```

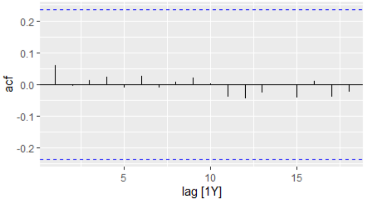
```
# A tibble: 1 x 2
  country ndiffs
  <chr>    <int>
1 China        0
```

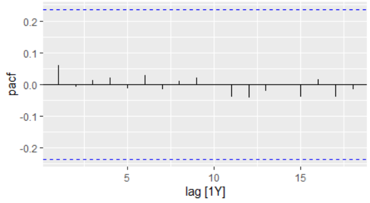
Figure 49 - USA's $(1-B)\log(GDP_{pc})$ series ACF and PACF plots and KPSS test result




```
# A tibble: 1 x 3
  country       kpss_stat kpss_pvalue
  <chr>             <dbl>       <dbl>
1 United States    0.0633         0.1
```

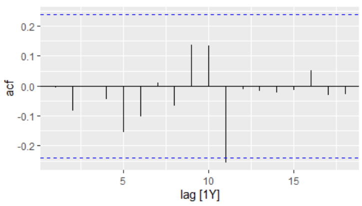
Figure 50 - Kuwait's $(1-B)\log(GDP_{pc})$ series ACF and PACF plots and KPSS test result

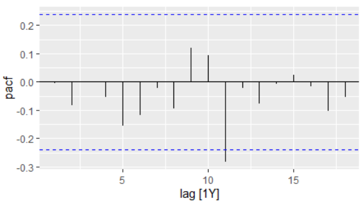




```
# A tibble: 1 x 3
  country kpss_stat kpss_pvalue
  <chr>       <dbl>       <dbl>
1 Kuwait      0.182         0.1
```

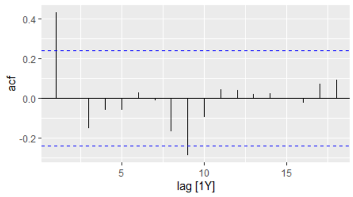
Figure 51 - Qatar's $(1-B)\log\left({CO_2}_{pc}\right)$ series ACF and PACF plots and KPSS test result

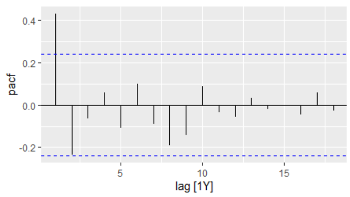




```
# A tibble: 1 x 3
  country kpss_stat kpss_pvalue
  <chr>       <dbl>       <dbl>
1 Qatar      0.0622         0.1
```

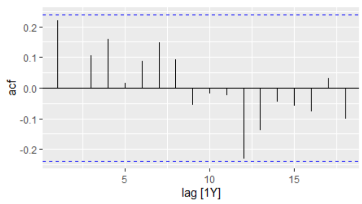
Figure 52 - China's $(1-B)\log\left({CO_2}_{pc}\right)$ series ACF and PACF plots and KPSS test result

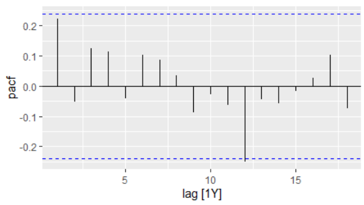




```
# A tibble: 1 x 3
  country          kpss_stat kpss_pvalue
  <chr>                <dbl>       <dbl>
1 CHINA (MAINLAND)     0.177         0.1
```

Figure 53 - USA's $(1-B)\log\left({CO_2}_{pc}\right)$ series ACF and PACF plots and KPSS test result





```
# A tibble: 1 x 3
  country                  kpss_stat kpss_pvalue
  <chr>                        <dbl>       <dbl>
1 UNITED STATES OF AMERICA     0.409      0.0733
```

```
# A tibble: 1 x 2
  country                  ndiffs
  <chr>                     <int>
1 UNITED STATES OF AMERICA      0
```

Figure 54 - China's $(1-B)\log(GDP_{pc})$ series ARIMA model selection and estimation

```
# A mable: 4 x 3
# Key:     country, Model name [4]
  country `Model name`           `Model order`
  <chr>   <chr>                        <model>
1 China   arima310               <ARIMA(3,1,0)>
2 China   arima013               <ARIMA(0,1,3)>
3 China   stepwise     <ARIMA(2,0,3) w/ mean>
4 China   search       <ARIMA(2,0,3) w/ mean>
```

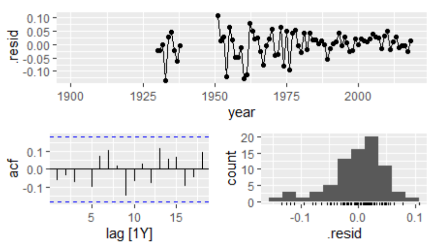
```
# A tibble: 4 x 6
  .model    sigma2 log_lik   AIC  AICc   BIC
  <chr>      <dbl>   <dbl> <dbl> <dbl> <dbl>
1 stepwise 0.00145    126. -237. -236. -218.
2 search   0.00145    126. -237. -236. -218.
3 arima013 0.00183    115. -222. -222. -211.
4 arima310 0.00210    110. -212. -211. -201.
```

```
Series: gdppc
Model: ARIMA(2,0,3) w/ mean

Coefficients:
          ar1      ar2     ma1     ma2     ma3  constant
      -1.6353  -0.8476  2.2426  2.0200  0.7375    0.1295
s.e.   0.0841   0.0840  0.0993  0.1668  0.0917    0.0310

sigma^2 estimated as 0.001449:  log likelihood=125.7
AIC=-237.4   AICc=-236.38   BIC=-218
```

Figure 55 - Histogram, ACF plot and Ljung-Box test results for the residuals of China's selected ARIMA model



```
# A tibble: 1 x 4
  country .model       lb_stat lb_pvalue
  <chr>   <chr>          <dbl>     <dbl>
1 China   ARIMA(gdppc)    5.52     0.356
```

Figure 56 - USA's $(1-B)\log(GDP_{pc})$ series selected ARIMA model estimation and residuals Ljung-Box test results

```
Series: gdppc
Model: ARIMA(0,0,1) w/ mean

Coefficients:
         ma1  constant
      0.2234    0.0165
s.e.  0.0879    0.0051

sigma^2 estimated as 0.002102:  log likelihood=197.28
AIC=-388.57   AICc=-388.36   BIC=-380.26
```

```
# A tibble: 1 x 4
  country       .model        lb_stat lb_pvalue
  <chr>         <chr>           <dbl>     <dbl>
1 United States ARIMA(gdppc)     11.9    0.0356
```

Figure 57 - Kuwait's $(1-B)\log(GDP_{pc})$ series selected ARIMA model estimation and residuals Ljung-Box test results

```
Series: gdppc
Model: ARIMA(0,0,0)

sigma^2 estimated as 0.1227:  log likelihood=-25.52
AIC=53.04   AICc=53.1   BIC=55.28
```

```
# A tibble: 1 x 4
  country .model       lb_stat lb_pvalue
  <chr>   <chr>          <dbl>     <dbl>
1 Kuwait  ARIMA(gdppc)   0.434     0.994
```

Figure 58 - Qatar's $(1-B)\log\left(CO_{2_{pc}}\right)$ series selected ARIMA model estimation and residuals Ljung-Box test results

```
Series: co2pc
Model: ARIMA(0,0,0)

sigma^2 estimated as 0.2169:  log likelihood=-43.87
AIC=89.73   AICc=89.8   BIC=91.94
```

```
# A tibble: 1 x 4
  country .model       lb_stat lb_pvalue
  <chr>   <chr>          <dbl>     <dbl>
1 Qatar   ARIMA(co2pc)    6.48     0.262
```

Figure 59 - China's $(1-B)\log\left(CO_{2_{pc}}\right)$ series selected ARIMA model estimation and residuals Ljung-Box test results

```
Series: co2pc
Model: ARIMA(0,0,1) w/ mean

Coefficients:
         ma1  constant
      0.4401    0.0578
s.e.  0.0894    0.0199

sigma^2 estimated as 0.01336:  log likelihood=50.42
AIC=-94.83   AICc=-94.45   BIC=-88.22
```

```
# A tibble: 1 x 4
  country            .model       lb_stat lb_pvalue
  <chr>              <chr>          <dbl>     <dbl>
1 CHINA (MAINLAND)   ARIMA(co2pc)    11.1    0.0486
```

Figure 60 - USA's $(1-B)\log\left(CO_{2_{pc}}\right)$ series selected ARIMA model estimation and residuals Ljung-Box test results

```
Series: co2pc
Model: ARIMA(0,0,1)

Coefficients:
         ma1
      0.2471
s.e.  0.1234

sigma^2 estimated as 0.0009364:  log likelihood=139.02
AIC=-274.03   AICc=-273.84   BIC=-269.62
```

```
# A tibble: 1 x 4
  country                   .model       lb_stat lb_pvalue
  <chr>                     <chr>          <dbl>     <dbl>
1 UNITED STATES OF AMERICA  ARIMA(co2pc)    4.46     0.485
```

Figure 61 - China's $(1-B)\log(GDP_{pc})$ series model selection and forecasts

```
# A tibble: 3 x 10
  .model      country .type      ME   RMSE    MAE
  <chr>       <chr>   <chr>   <dbl>  <dbl>  <dbl>
1 arima       China   Test   0.0218 0.0403 0.0314
2 exponential China   Test   0.0178 0.0515 0.0376
3 regression  China   Test   0.0761 0.166  0.0900
```

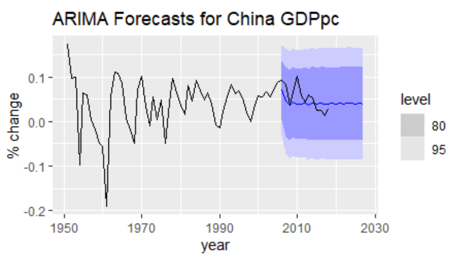


Figure 62 - USA's $(1-B)\log(GDP_{pc})$ series model selection and forecasts

```
# A tibble: 3 x 10
  .model      country       .type      ME   RMSE    MAE
  <chr>       <chr>         <chr>   <dbl>  <dbl>  <dbl>
1 arima       United States Test  0.00880 0.0462 0.0328
2 exponential United States Test  0.00194 0.0454 0.0318
3 regression  United States Test  0.00949 0.0572 0.0376
```

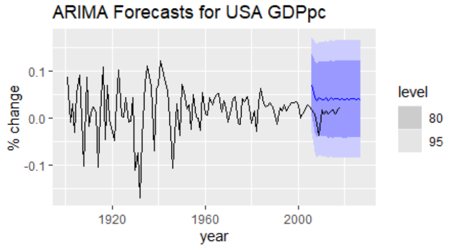


Figure 63 - Kuwait's $(1-B)\log(GDP_{pc})$ series model selection and forecasts

```
# A tibble: 3 x 10
  .model      country .type     ME  RMSE   MAE
  <chr>       <chr>   <chr>  <dbl> <dbl> <dbl>
1 arima       Kuwait  Test  0.0168 0.176 0.113
2 exponential Kuwait  Test  0.0327 0.220 0.153
3 regression  Kuwait  Test  0.0656 0.205 0.147
```

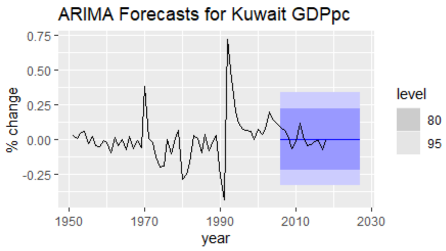


Figure 64 - Qatar's $(1-B)\log\left(CO_{2_{pc}}\right)$ series model selection and forecasts

```
# A tibble: 3 x 10
  .model                                     country .type      ME  RMSE   MAE
  <chr>                                      <chr>   <chr>   <dbl> <dbl> <dbl>
1 "ARIMA(CO2pc ~ pdq(0, 0, 0))"              Qatar   Test   0.0194 0.462 0.171
2 "ETS(CO2pc ~ error(\"A\") + trend(\"Ad\"))" Qatar   Test  -0.0297 0.516 0.239
3 "TSLM(CO2pc ~ trend())"                    Qatar   Test  -0.0408 0.538 0.264
```

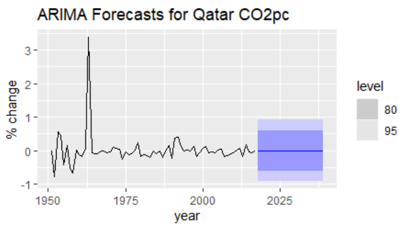


Figure 65 - China's $(1-B)\log\left(CO_{2_{pc}}\right)$ series model selection and forecasts

```
# A tibble: 3 x 10
  .model                                     country           .type      ME   RMSE    MAE
  <chr>                                      <chr>             <chr>   <dbl>  <dbl>  <dbl>
1 "ARIMA(CO2pc ~ pdq(0, 0, 1))"              CHINA (MAINLAND) Test  0.00187 0.0716 0.0538
2 "ETS(CO2pc ~ error(\"A\") + trend(\"Ad\"))" CHINA (MAINLAND) Test  0.00688 0.211  0.115
3 "TSLM(CO2pc ~ trend())"                    CHINA (MAINLAND) Test  0.0516  0.289  0.173
```

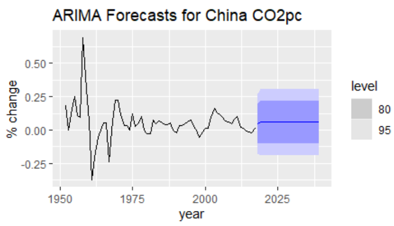


Figure 66 - USA's $(1-B)\log\left(CO_{2_{pc}}\right)$ series model selection and forecasts

```
# A tibble: 3 x 10
  .model                                     country                  .type        ME   RMSE    MAE
  <chr>                                      <chr>                    <chr>     <dbl>  <dbl>  <dbl>
1 "ARIMA(CO2pc ~ pdq(0, 0, 1))"              UNITED STATES OF AMERICA Test  0.0000643 0.0295 0.0237
2 "ETS(CO2pc ~ error(\"A\") + trend(\"Ad\"))" UNITED STATES OF AMERICA Test -0.00600   0.0330 0.0240
3 "TSLM(CO2pc ~ trend())"                    UNITED STATES OF AMERICA Test -0.00760   0.0312 0.0225
```