Forecasting the unemployment rate using the Okun relationship

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Abstract

In this paper, I forecast the unemployment rate using Okun's relationship. I use a dataset containing the yearly data over the period 1985-2020, where I use the period 1985-2010 as a training set to forecast the period 2011-2020. I create two models with fixed coefficients, two rolling window models and two adjusted autoregressive models which make all use of the Okun relationship. I measure the forecast performance of the four models by comparing the Mean Absolute Error (MAE) and the Mean Squared Error (MSE) of these models with these of an ARIMA model. I find that the union density, the wage coordination, the tax wedge and the terms of trade of the current year significantly affect the unemployment rate of the following year. Although the adjusted autoregressive models forecast more accurate than the fixed and rolling window models, none of the models managed to outperform the ARIMA model. Finally, I find that the unemployment rate can be forecasted more accurate for older people than the unemployment rate for younger people.

Contents

1 Introduction

In 1962, Okun presented his article where he found the relationship between the unemployment rate and the growth of output, measured by the GDP. This negative relationship is also known as 'Okun's law'. In this research, I want to use this relationship in forecasting the unemployment rate. Policymakers need to predict the unemployment in the following period, as it is crucial for the country's economic and financial growth planning. If a high unemployment rate is expected, socio-economic problems can be recognized early and thus may be reduced (Chakraborty et al., 2021).

In this paper, I investigate whether the GDP gap of the current year helps to predict the unemployment rate of the following year. The research question is as follows: *'Is Okun's law useful to forecast the unemployment rate and can a model using Okun's law outperform currently used models?'*.

To answer this question, I make use of an extended version of the dataset Dixon et al. (2017) used. This dataset contains data for 20 OECD countries, of which 15 are European, over the period between 1971 and 2020. Since all the variables needed are complete in the dataset over the period 1985-2020, the research is focused on this timeframe. I create six models that make use of Okun's law. First, I look at two models where the coefficients are fixed over time. I estimate these coefficients over the training set, and I use these estimates to forecast the test set. In the first model, I only use the GDP gap as an explanatory variable. Next to the GDP gap, Dixon et al. (2017) also found a significant effect of the union density, the wage coordination, the tax wedge, and the terms of trade. I investigate whether the values of these variables for the current year affect the unemployment rate of the following year. In the second model, I add these four variables since they all have a significant effect.

Knotek II (2007) suggests that Okun's law can be a useful tool in forecasting the unemployment rate changes, but we have to take into account that the effect of changes in GDP has a different effect at different times. Therefore, I also look at two models where I allow the coefficients to change over time in two rolling window models. In the first rolling window model, I again only use the GDP gap as an explanatory variable. The second rolling window also contains the effects of the union density, the wage coordination, the tax wedge and the terms of trade. Finally, I create two adjusted autoregressive models. The GDP gap again is the only explanatory variable of the first adjusted autoregressive model, and for the second adjusted autoregressive model, I add the same variables as I add in the second fixed model and the second rolling window model.

The forecast performance of the four models is measured with the Mean Absolute Error

(MAE) and the Mean Squared Error (MSE). I use an Autoregressive Integrated Moving Average (ARIMA) model as a benchmark for the forecast performances of the other models since this linear model is often used as a benchmark when forecasting the unemployment rate. (Chakraborty et al., 2021; Montgomery et al., 1998; Proietti, 2003)

This research is of added value to the existing literature, as I use Okun's law in forecasting the unemployment rate. Pierdzioch et al. (2011) did this for the G7 countries and found that Okun's law is useful for forecasting the unemployment rate. I want to determine if this is also useful in 20 OECD countries. To my knowledge, there is not done any research using Okun's law to forecast the unemployment rate, next to Pierdzioch et al. (2011).

We find that the union density, the wage coordination, the tax wedge, and the terms of trade of the current year, significantly influence the unemployment rate of the next year. Adding these variables to the model with only the GDP gap as an explanatory variable does make worse forecasts for the fixed coefficient model and the rolling window model. Estimating the coefficients over a rolling window leads to more accurate forecasts for the model with only the GDP gap as an explanatory variable. However, these forecasts are strictly outperformed by the ARIMA model for each country.

Adding these four variables does increase the forecast performance of the adjusted autoregressive model. The adjusted autoregressive models forecast the unemployment rate more accurately than the models with fixed coefficients and the rolling window models, but they still do not beat the forecasts of the ARIMA model. Although for some countries the rolling window models forecast more accurately, the ARIMA model predicts more accurately for the biggest part of the countries. The adjusted autoregressive model which uses the GDP gap, the union density, the wage coordination, the tax wedge and the terms of trade as explanatory variables gives the most accurate forecasts out of the six models using the Okun relationship.

I use the second adjusted autoregressive model and the ARIMA model to forecast different age groups. I find that the youngest age group (between 15 and 24 years old) is the most difficult to forecast for these models. This is caused by a higher and more volatile unemployment rate for this age group.

This paper is structured as follows. In the next section, I provide an overview of the existing literature about the relationships between the variables I want to use and the unemployment rate, together with some theories about forecasting the unemployment rate. In Section 3 I describe the dataset I use for this research. After that, I explain which models I use to forecast and how the performance of these models will be measured in Section 4. In Section 5 I give the results of the research and Section 6 concludes.

2 Theoretical background

Since the publication of Okun's law, a lot of research has been done if this relationship still holds, or which other variables might influence the unemployment rate. Knotek II (2007) researched the period 1945-2007 and found that Okun's law does not always hold for some short time or long time periods. Therefore, he suggests using Okun's law more as a rule of thumb than as a stable relationship over time. An implication of this is that when using Okun's law in forecasting, forecasts can be improved by taking this changing nature into account. In addition, Lal et al. (2010) also find that Okun's law may not be applicable when looking at Asian developing countries. Most of the research that has been done when reconsidering Okun's law, looked at OECD countries, as these countries typically are democratic and support free-market economies. For instance, Kargi (2014) and Lee (2000) find that Okun's law is valid when looking at OECD countries. Therefore, in this research, I only want to forecast the unemployment rate of OECD countries.

Where Adams & Coe (1990), Scarpetta (1996) and Dixon et al. (2017) find a significant positive relationship between the unemployment rate and union density, Bassanini & Duval (2009) do not find a significant relationship. That said, they did find a significant positive effect of the tax wedge. Šeparović (2009) also researched how the tax wedge affects the unemployment rate and found that an increase in the tax wedge increases a company's labour costs and thus indirectly influences the unemployment. Compared to the OECD countries, Croatia has a higher tax wedge, which is one of the reasons for the high unemployment. He suggests Croatia to work on the reduction of the tax wedge to let the unemployment rate also drop.

According to Dixon et al. (2017), the level of wage coordination negatively affects the unemployment rate. So, if a particular country has binding norms, the unemployment rate is expected to be lower than when this country has no wage coordination at all. They also find a negative effect of the terms of trade, which is the ratio of a country's import and export prices. Scarpetta (1996) also finds this effect and argues that this is caused by the gap between value-added prices and consumer prices as a consequence of the terms of trade that have become worse. This would then affect the unemployment rate.

When forecasting the unemployment rate, the ARIMA model is used often as a linear benchmark (Chakraborty et al., 2021; Montgomery et al., 1998; Proietti, 2003). Proietti (2003) uses Markov switching models and Chakraborty et al. (2021) use some hybrid ARIMA models. Both researches find a better alternative for the ARIMA model, as their models forecast more accurate. This suggests the ARIMA model is a solid benchmark, but it should not be approached as an upper bound.

3 Data

The dataset I use contains the same variables as the dataset Dixon et al. (2017) use, but the time frame is extended. This dataset contains data for 20 OECD countries over the period 1971-2020, whereas the dataset of Dixon et al. (2017) contains the period 1985-2013. For every country and year, the dataset contains certain variables which might influence the unemployment rate. For instance, the GDP gap, the average temporary jobs, the union density, and the tax wedge. I also have data available that specifies the unemployment rates for each age group and gender. The 20 OECD countries I look at, contain 15 countries in Europe, of which 10 countries are using the Euro as currency (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal and Spain) and five European countries which are not using the Euro (Denmark, Norway, Sweden, Switzerland and the United Kingdom). Next to these 15 countries I also look at five countries outside Europe (Australia, Canada, Japan, New Zealand and the United States).

In my research, I look at the period between 1985 and 2020, because not all the data is available for the variables I want to use in the period before 1985. Some summary statistics are given in Table 1 for the unemployment rate and the GDP gap for each country I use. There are some big differences in the mean unemployment rate. Especially Spain has a high unemployment rate, while Ireland got the highest standard deviation of unemployment rates of all countries. This suggests it would be harder to forecast the unemployment rate accurately for Ireland. All the means of the GDP gap are approximately zero, which makes sense since the variable contains the difference in output from the year before. A mean of around zero suggests the series are stable over time. Again Ireland has got the highest standard deviation of all countries.

Table 1: Unemployment rate and GDP gap statistics over the period 1985-2020.

	Unemployment rate		**GDP gap**	
	Mean	Standard deviation	Mean	Standard deviation
Australia	6.694	1.726	0.000	1.875
Austria	4.644	0.858	0.000	2.904
Belgium	8.100	1.482	0.000	2.401
Canada	8.014	1.569	0.000	3.234
Denmark	6.322	1.697	0.000	2.874
Finland	9.158	3.615	0.000	5.141
France	9.794	1.417	0.000	2.854
Germany	6.950	2.212	0.000	2.770
Ireland	10.492	5.042	0.000	19.952
Italy	10.325	1.833	0.000	2.817
Japan	3.592	1.012	0.000	3.012
Netherlands	5.844	2.452	0.000	3.338
New Zealand	5.931	1.861	0.000	3.279
Norway	3.992	1.090	0.000	2.571
Portugal	7.653	3.262	0.000	4.898
Spain	17.469	4.990	0.000	6.063
Sweden	6.472	2.431	0.000	3.425
Switzerland	3.389	1.450	0.000	2.264
United Kingdom	6.881	2.197	0.000	4.516
United States	5.992	1.545	0.000	3.275

Figure 1 shows the relationship between the unemployment rate and the GDP gap between 1985 and 2020. For every year, the unemployment rate and GDP gap are calculated by the mean of the 20 countries. The GDP gap is given a negative sign because of the negative relationship. Figure 1 shows that the unemployment rate and the GDP gap are probably related, as the lines move close to each other. There is a steep incline after 2008, which is also known as the great recession.

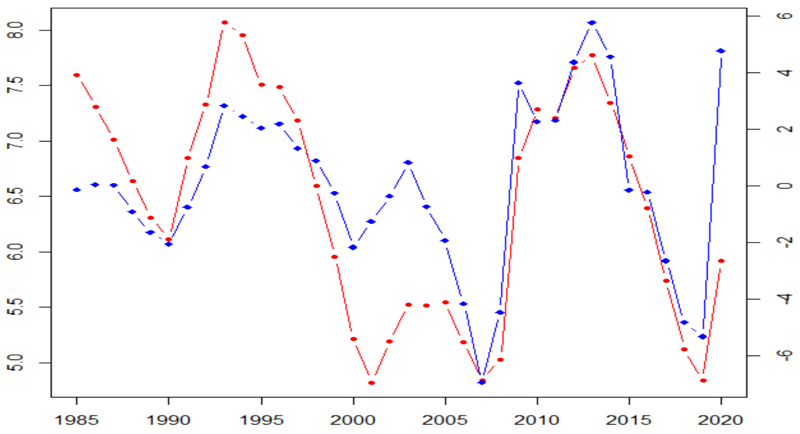

Figure 1: Relationship between the mean unemployment rate and the mean negative GDP gap between 1985 and 2020 over the 20 countries.
The value of the unemployment rate is given by the left axis and the value of the negative GDP gap is given by the right axis.

4 Methodology

4.1 Forecasting models

First, I forecast the unemployment rate using two models with fixed coefficients over time. In these models, I estimate the coefficients based on a training set (1985-2010) and use these estimates to forecast the observations in the test set (2011-2020). Thereafter, I continue by allowing these coefficients to change over time in two rolling window models. After that, I introduce two adjusted autoregressive (AR) models. Finally, I explain how I use the ARIMA model as a benchmark for the forecast models that are using Okun's relationship.

4.1.1 Fixed models

The baseline model I use is a model where I only look at the effect of the GDP gap, later called 'Fixed Model 1'. I estimate the coefficients by an OLS regression in R. In Fixed Model 1, the unemployment rate is forecasted by

$$u_{i,t} = \alpha_i - \gamma_y y_{i,t-1}, \tag{1}$$

where $u_{i,t}$ is the unemployment rate of country i in year t, $y_{i,t}$ is the GDP gap of country i in year t, and α_i is a country fixed effect, in this case, the equilibrium unemployment rate. γ_y

is also called the Okun coefficient and since I add a negative sign, I expect this coefficient to be positive.

To expand this model, I add four variables if the values of the current year significantly affect the unemployment rate of the following year. To decide which variables to add, and which variables not, I perform a panel GLS regression in Eviews, in the same way Dixon et al. (2017) did. If I include all four variables, I forecast the unemployment rate with Fixed Model 2 as

$$u_{i,t} = \alpha_i - \gamma_y y_{i,t-1} + \gamma_d d_{i,t-1} - \gamma_w w_{i,t-1} + \gamma_x x_{i,t-1} - \gamma_z z_{i,t-1}, \tag{2}$$

where $d_{i,t}$ is the union density, given by the proportion of employees who are member of a trade union among all employees of country i in year t. The wage coordination is given by $w_{i,t}$, which takes values from 1 to 5 (low to high). Here 1 is fragmented wage bargaining, no coordination, and 5 means binding norms. $x_{i,t}$ gives the tax wedge, this is the average tax wedge of a one-earner married couple at 100% of average earnings with two children. The terms of trade is calculated by $z_{i,t} = (\frac{T_{i,t}}{T_{i,t-1}} - 1) * 100$, where $T_{i,t}$ is the deflator export divided by the deflator import of country i in year t. d_{it}, $w_{i,t}$, x_{it} and $z_{i,t}$ are all demeaned. Since Dixon et al. (2017) found negative effects of the wage coordination and the terms of trade, I added negative signs for these variables. In this way, I expect all the coefficients to be positive. If the forecasted unemployment rate is below 0, I assign the value of 0.001 to it as the unemployment rate cannot be negative.

4.1.2 Rolling window models

Since Knotek II (2007) advises that taking into account the changing nature of Okun's law would improve the forecast, I allow the coefficients to change over time in two rolling window models. In RW Model 1, I use the same model as Fixed Model 1, but to forecast the unemployment rate of year t, the coefficients will be estimated over the period between $t-1$ and $t-11$. In the same way, I create RW Model 2 by using Fixed Model 2.

4.1.3 Adjusted autoregressive models

In the first adjusted autoregressive model (AAR Model 1) I use, I do not use the equilibrium unemployment anymore, but I use the unemployment rate of the year before. To forecast the unemployment rate $u_{i,t}$, the coefficients are estimated for each country i individually over the period between $t-11$ and $t-1$. In this way, I forecast the unemployment rate as

$$u_{i,t} = \beta_u u_{i,t-1} + \beta_y y^*_{i,t-1}, \tag{3}$$

where $y^*_{i,t}$ is the difference in GDP gap between year t and year $t-1$. I expand this model by again using the same four variables as in the models explained before. In this way, I get a second adjusted autoregressive model (AAR Model 2), that is given by

$$u_{i,t} = \beta_u u_{i,t-1} + \beta_y y^*_{i,t-1} + \beta_d d^*_{i,t-1} + \beta_w w^*_{i,t-1} + \beta_x x^*_{i,t-1} + \beta_z z^*_{i,t-1}, \tag{4}$$

where the variables $d^*_{i,t}$, $w^*_{i,t}$, $x^*_{i,t}$ and $z^*_{i,t}$ all contain the one-year difference between year t and $t-1$.

4.1.4 Benchmark model

In the current literature, the ARIMA model is often used as a benchmark when forecasting the unemployment rate (Chakraborty et al., 2021; Montgomery et al., 1998; Proietti, 2003). For this reason, I want to compare the other models with this ARIMA model. I need the parameters p, d, and q. p is the order of the AR model, q is the order of the MA model and d is the level of differencing. The unemployment rate will be forecasted by an ARIMA(p,d,q) model as

$$u_{i,t} = \delta_i + \sum_{k=1}^{p} \phi_{i,k} u_{i,t-k} + \sum_{j=1}^{q} \theta_{i,j} \epsilon_{i,t-j}, \tag{5}$$

where $\epsilon_{i,t}$ is the random error of country i in year t. To decide the values of the parameters, I look at the autocorrelation function (ACF) and the partial autocorrelation function (PACF) for each country and find the best-fitted model using Akaike information criterion (AIC) and Bayesian information criterion (BIC). I do this for each country individually, so probably each country gets different parameters and coefficients.

4.2 Forecasting performance

To compare the different models, I use two types of scores to measure the forecast performance of the models. First, I use the Mean Absolute Error (MAE), given in Equation 6 when calculating the score over a period of n years, starting in year s.

$$MAE = \frac{1}{n} \sum_{j=s}^{s+n} |e_j|, \tag{6}$$

where e_j is the error of the forecast in year j. I also look at the Mean Squared Error (MSE). Where the MAE gives the same weight to each error, the MSE gives a higher weight to a worse forecast. I calculate the MSE as

$$MSE = \frac{1}{n} \sum_{j=s}^{s+n} e_j^2. \tag{7}$$

5 Results

5.1 Estimation

First, I estimate the coefficients over all countries with a panel GLS regression in Eviews, to see which variables to include. Table 2 shows that the GDP gap, the union density, the wage coordination, the tax wedge and the terms of trade all significantly affect the unemployment rate. Since I add negative signs to γ_y, γ_w and γ_z, all coefficients have positive values. As explained before, the Okun coefficient is given by γ_y. In Fixed Model 1, it takes the value of 0.274. This means if the GDP gap increases by 1, the unemployment rate would drop by 0.274, because of the negative sign. The added variables in Fixed Model 2 take away some effect of the GDP gap, since γ_y declines from 0.274 to 0.199.

Table 2: Estimation of the coefficients over all countries for Fixed Model 1 and Fixed Model 2 based on the period 1985-2010. Estimation is done with a panel GLS regression in Eviews.

Coefficient	**Fixed Model 1**	**Fixed Model 2**
$\bar{\alpha}$	7.484***	7.302***
γ_y	0.274***	0.199***
γ_d		0.035**
γ_w		0.623***
γ_x		0.148***
γ_z		0.039***

**** Significant with p-value smaller than 0.01.*

*** Significant with p-value smaller than 0.05.*

To forecast the period 2011-2020, I do not allow the coefficients to vary over time, but I do allow them to differ for different countries. Table 3 shows α_i for each country i. In Fixed Model 1, α_i is equal to the equilibrium unemployment rate of country i. As shown in Table 1, Spain has the highest unemployment rate and Switzerland has the lowest.

Table 3: Intercept for all 20 countries for the two fixed models based on the period 1985-2010.

Country	α_i **in Fixed Model 1**	α_i **in Fixed Model 2**
Australia	7.081	8.147
Austria	4.445	4.03
Belgium	8.356	8.885
Canada	8.330	9.193
Denmark	6.420	7.088
Finland	10.000	9.577
France	10.010	10.769
Germany	7.948	7.311
Ireland	11.095	14.007
Italy	10.229	11.486
Japan	3.737	2.977
Netherlands	5.821	7.129
New Zealand	6.509	7.171
Norway	4.227	4.408
Portugal	6.305	5.545
Spain	16.655	19.254
Sweden	6.281	5.646
Switzerland	2.966	2.386
United Kingdom	7.339	8.402
United States	5.957	5.866

For deciding which values to take for parameters p, d and q in the ARIMA(p,d,q) models, I use the 'forecast' package in R, in the same way Chakraborty et al. (2021) did. The values of p and q are based on the ACF and PACF in Table 7-10 in the Appendix and vary for each country. The value of d is determined by an Augmented Dickey-Fuller (ADF) test for stationarity check, and the best fit of each model is chosen for the lowest AIC and BIC. In this way, different ARIMA models are created for each country and year, to make one-year ahead forecasts.

5.2 Forecasting

The forecast performance scores of the fixed models are given in Table 4, together with the performance scores of the ARIMA model. What stands out, is that Fixed Model 2 performs worse than Fixed Model 1, while I expected it to perform better since Fixed Model 2 has four more explanatory variables. There are two possible causes. First, the test set is too small to get acceptable estimates if I only look at the period 1985-2010 for just one country. The second possibility is caused by the values of one of the added variables. The wage coordination is given a value between 1 and 5. For many countries, the value of the wage coordination stays the same for a long time. When it subsequently changes, it is given a too large effect and the forecast has a big error. So, Fixed Model 1 performs better than Fixed Model 2, but the forecast performance does not come close to the ARIMA model. Where Fixed Model 1 is on average 1.753 far away from the real unemployment rate, the ARIMA model is only 0.558 away.

Table 4: Forecast performance scores of the fixed models, compared with the forecast performance scores of the ARIMA model over the period 2011-2020.

Country	**Fixed Model 1**		**Fixed Model 2**		**ARIMA**	
	MAE	MSE	MAE	MSE	MAE	MSE
Australia	1.386	2.485	4.726	22.704	0.411	0.324
Austria	0.864	0.984	1.458	2.594	0.440	0.294
Belgium	0.923	1.167	1.682	3.387	0.598	0.517
Canada	1.626	2.839	2.243	5.277	0.544	1.517
Denmark	0.728	0.878	1.356	2.270	0.363	0.185
Finland	2.424	7.380	1.804	4.331	0.754	0.974
France	0.875	1.240	1.377	2.164	0.377	0.173
Germany	3.426	12.276	1.882	3.928	0.451	0.285
Ireland	3.686	22.101	10.664	130.651	1.141	1.942
Italy	1.069	1.536	2.066	5.724	0.664	0.897
Japan	0.493	0.346	1.658	3.309	0.239	0.074
Netherlands	0.684	0.744	2.386	8.284	0.693	0.577
New Zealand	1.841	4.238	5.621	34.639	0.411	0.253
Norway	1.027	1.789	1.023	1.650	0.341	0.194
Portugal	4.747	30.792	5.598	42.876	1.015	2.207
Spain	3.071	14.835	3.503	13.933	0.750	1.234
Sweden	1.379	2.966	5.476	32.763	0.358	0.279
Switzerland	1.794	3.262	2.935	8.762	0.231	0.096
United Kingdom	1.547	2.769	3.971	16.496	0.447	0.335
United States	1.478	2.875	2.560	11.260	0.926	2.068
Total	1.753	5.875	3.199	17.850	**0.558**	**0.721**

In other words, the fixed models do not forecast well. One reason for this may be that the coefficients could change over time. To solve this problem, I now look at the forecast performance of the rolling window models, where I allow coefficients to be different for each year. Since the wage coordination frequently has the same value for multiple years, estimating over an eleven-year time frame often leads to errors for this variable. Therefore, I decided to let the wage coordination out of RW Model 2. Table 5 shows that the first rolling window model performs better than the first fixed model. However, the performance scores of RW Model 2 are higher than those of Fixed Model 2. In particular, the MSE of RW Model 2 is high. These high scores are mainly caused by the scores for Ireland, which has a MAE of 16.906 and a MSE of 433.733. We can conclude that a rolling window model does improve the forecast performance of the first model, which only includes the Okun relationship. This is in line with the findings of Knotek II (2007), who advised taking into account the changing nature of the Okun relationship. On the other side, using a rolling window model when also using the tax wedge, the union density and the terms of trade, leads to less accurate forecasts.

Table 5: Forecast performance scores of the two rolling window models and the two adjusted autoregressive models, compared with the forecast performance scores of the ARIMA model over the period 2011-2020.

	RW Model 1	**RW Model 2**	**AAR Model 1**	**AAR Model 2**	**ARIMA**
MAE	1.329	3.268	0.841	0.783	**0.558**
MSE	4.695	35.089	1.583	1.385	**0.721**

Table 5 shows that the performance scores of the adjusted autoregressive models are more close to the scores of the ARIMA model than the fixed and rolling window models. What stands out, is that adding the extra four economic variables now leads to better forecast performance. This was not the case for the fixed and rolling window models. The MAE and MSE for each country are given in Figure 2 and Figure 3. The ARIMA model is the lowest in both figures, which means it has the best scores, for almost all countries. However, the ARIMA model does not strictly outperform the adjusted autoregressive models, since there are a couple of countries where one of the adjusted autoregressive models gives a more accurate forecast. What stands out, is that again Ireland and Spain, are hard to forecast for the adjusted autoregressive models compared to the ARIMA model. These countries have the highest variance in unemployment rates. Although the performance scores of the adjusted autoregressive models are notably better than those of the fixed and rolling window models, I still do not find an improvement for the ARIMA model.

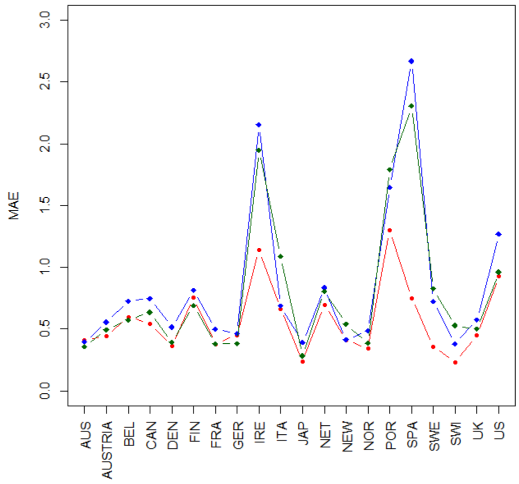

Figure 2: MAE for the two autoregressive models and the ARIMA model for each country when forecasting the unemployment rate over the period 2011-2020.
AAR Model 1 is given by the blue line, AAR Model 2 is given by the green line and the ARIMA model is given by the red line.

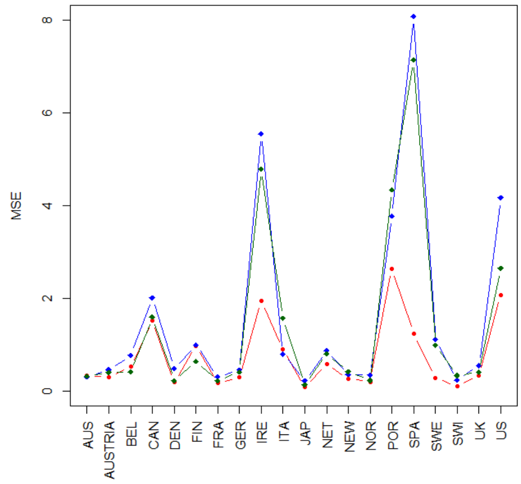

Figure 3: MSE for the two autoregressive models and the ARIMA model for each country when forecasting the unemployment rate over the period 2011-2020.
AAR Model 1 is given by the blue line, AAR Model 2 is given by the green line and the ARIMA model is given by the red line.

5.3 Forecasting different age groups

Since AAR Model 2 is the best performing model using Okun's relationship, I use this model, together with the ARIMA model to forecast the unemployment rates for different age groups. Since the data is split into male unemployment rates and female unemployment rates for the different age groups, I assume that there are as many men as women. So, when calculating the unemployment rate for an age group, I take the average of the male and female unemployment rate for that age group. Table 6 shows the performance scores and the ARIMA model again makes the most accurate forecasts for all age groups. The forecasts are more accurate when people get older. Especially the MAE and MSE of the forecasts for the people between 15 and 24 are much higher than those for the older age groups. I could expect this since the unemployment of this age group is on average higher and more volatile, which can be seen in Figure 4. Following O'higgins (1997), this is caused by a lack of company-specific skills compared to older workers. In addition, younger people also have less protection when getting fired than older people and are less likely to need to earn money to support their family.

Table 6: Forecast performance scores of RW Model 2 and the ARIMA model when forecasting different age groups over the period 2011-2020

Age group	**RW Model 2**		**ARIMA**	
	MAE	MSE	MAE	MSE
15-24	1.713	6.391	1.226	3.276
25-54	0.697	1.134	0.557	0.699
55-64	0.634	0.961	0.537	0.693

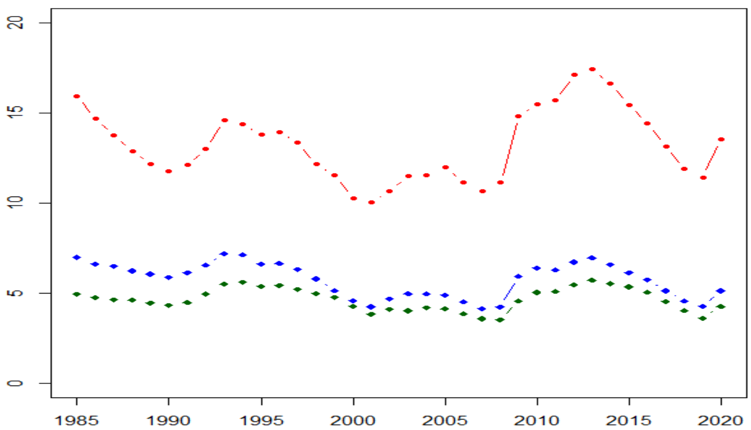

Figure 4: The unemployment rate over time given for different age groups. The age group of 15-24 years old people is given by the red line, the age group of 25-54 years old people is given by the blue line and the age group of 55-64 years old people is given by the green line.

6 Conclusion

In this paper, I want to answer the research question *'Is Okun's law useful to forecast the unemployment rate and can a model using Okun's law outperform currently used models?'*. I do this by creating different models where the GDP gap of the current year is one of the explanatory variables for the unemployment rate of the following year. The coefficients of the first two models are fixed, while I allow the coefficients in the third and fourth model to differ over time. The fifth and sixth model are autoregressive models, which are adjusted with explanatory variables. I compare these models with an ARIMA model, which is a linear time series model.

The first two models have fixed coefficients that are estimated over the period 1985-2010. With these estimates, I forecast the unemployment rates over the period 2011-2020. In the first model, I forecast the unemployment rate of the following year for each country by the equilibrium unemployment rate of that country, together with the GDP gap of the current year. In the second model, I add the following four demeaned explanatory variables to this model since they affect the unemployment rate significantly: the union density, the wage coordination, the tax wedge and the terms of trade. The coefficients for these variables are also fixed over time.

The third and fourth model are rolling window models. The models are the same that are used in the fixed models, but I estimate the coefficients based on the 11 years before. In the fifth model, I create an adjusted autoregressive model by estimating the unemployment rate for the following year by the unemployment rate and the GDP gap of the current year. I again extend this model by adding the same four variables as in the second model, but this time I take the one-year difference instead of the demeaned value.

To compare the six models with the ARIMA model, I measure the forecast performance with two different performance scores. I make use of the MAE to see the mean error of the forecasts, and I look at the MSE to give bigger errors a higher weight.

When comparing the models with fixed coefficients, I see that the first model surprisingly forecasts better than the first model, but both models do not come close to the forecast performance of the ARIMA model. The ARIMA model strictly dominates the two models with fixed coefficients, since the unemployment rate of no country is forecasted more accurate than the forecasts of the ARIMA model.

The first rolling window model performs better than the first fixed model. This suggests the Okun coefficient changes over time. However, the second rolling window model performs worse than the second fixed model.

The forecasts of the adjusted autoregressive models are far more accurate than those of the fixed coefficient en rolling window models. Although for some countries the adjusted autoregressive models forecast more accurately, the ARIMA model performs the best overall, since the MAE and MSE both are lower on average over all countries.

Finally, I use the second adjusted autoregressive model and the ARIMA model to forecast the unemployment rate for three different age groups. For older people, the unemployment rate can be forecasted more accurately than for younger people. This is due to a higher and more volatile unemployment rate for this younger group, which may be caused by a lack of company-specific skills, less protection when they get fired and younger people are also less likely to need to earn money to take care of a family.

To answer the research question, the best model I find using Okun's law is an adjusted autoregressive model which also uses some more economic explanatory variables. However, this model does not outperform the ARIMA model, which is used often in existing theory.

A limitation of this research is the size of the dataset. I use the period between 1985 and 2020, but since I need a training set and a test set, I only forecasted the unemployment rate for ten years. With a larger dataset, I could forecast a larger timeframe including different economic cycles. Further research can also be done in finding different models using Okun's law. A hybrid model can be created where the ARIMA model can be combined with the effect of the GDP gap. This maybe could improve the forecast performance of the ARIMA model.

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Appendix

Table 7: ACF and PACF for the first five countries

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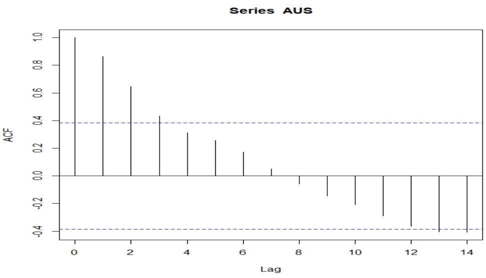
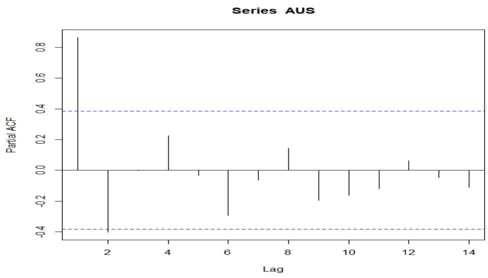
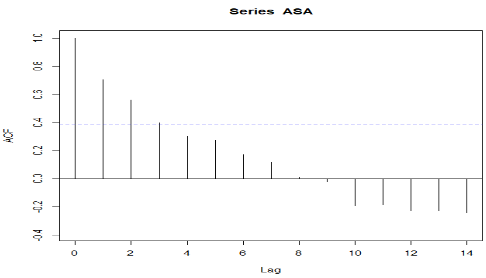
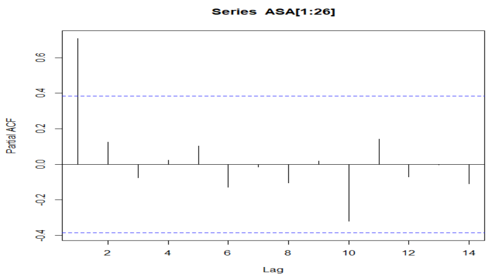
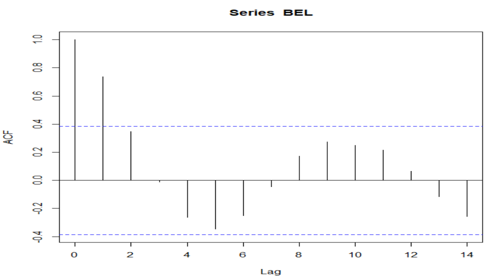
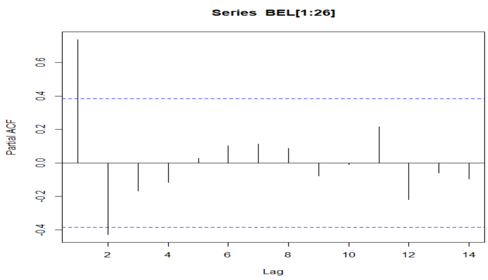
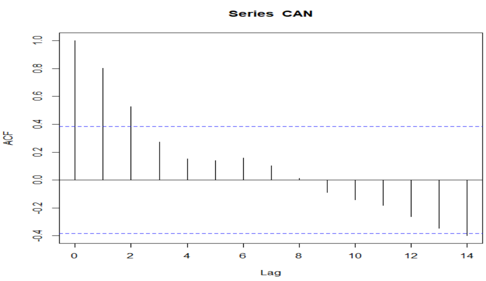
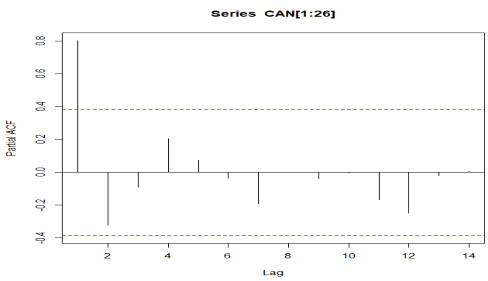
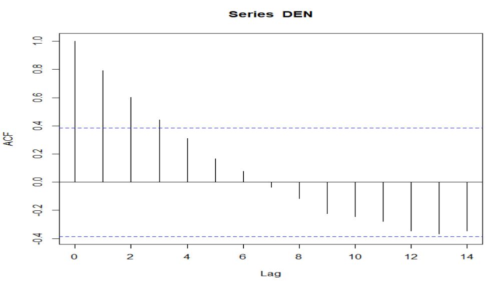
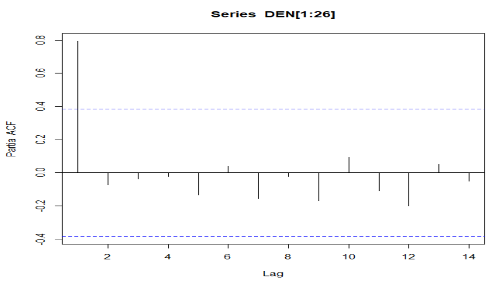
<tr><th>Country</th><th>ACF</th><th>PACF</th></tr>
<tr><td>Australia</td><td></td><td></td></tr>
<tr><td>Austria</td><td></td><td></td></tr>
<tr><td>Belgium</td><td></td><td></td></tr>
<tr><td>Canada</td><td></td><td></td></tr>
<tr><td>Denmark</td><td></td><td></td></tr>
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Table 8: ACF and PACF for the second five countries

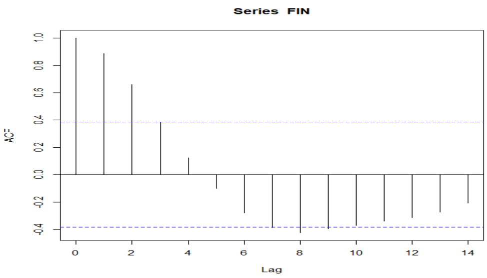
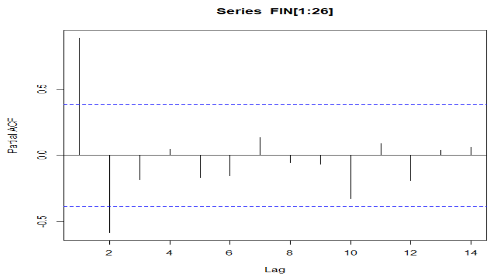
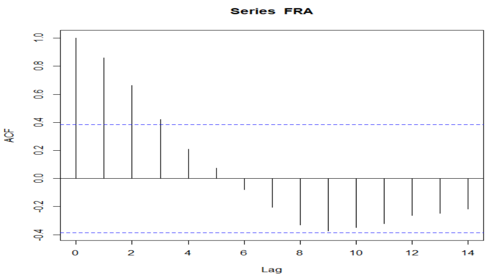
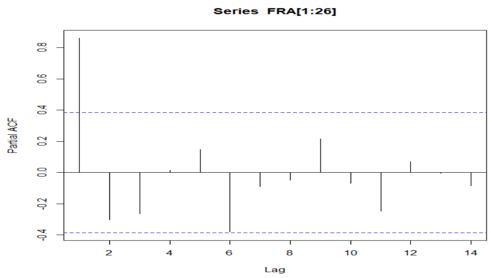
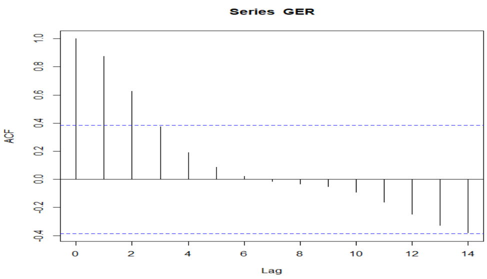
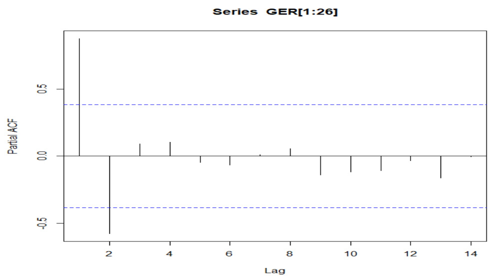
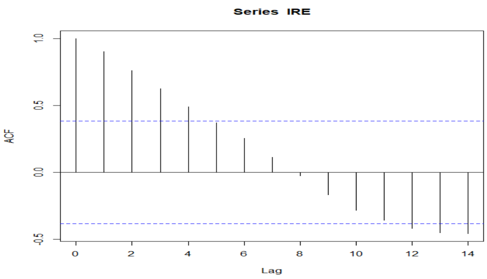
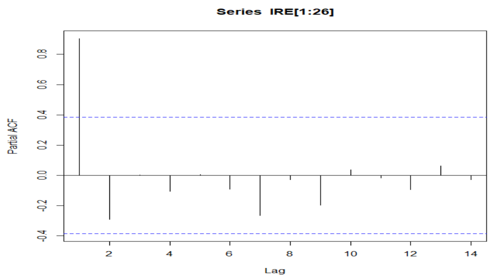
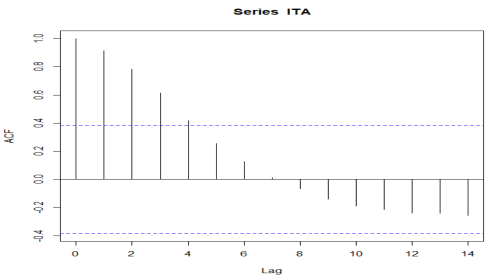
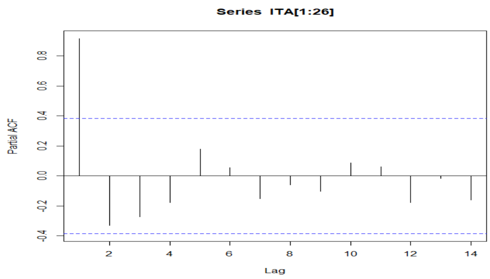
Country	ACF	PACF
Finland		
France		
Germany		
Ireland		
Italy		

Table 9: ACF and PACF for the third five countries

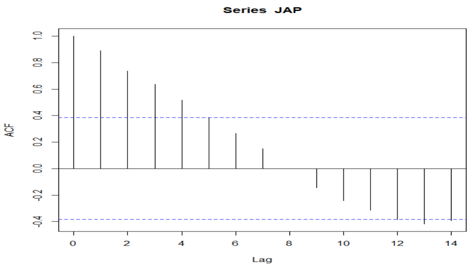
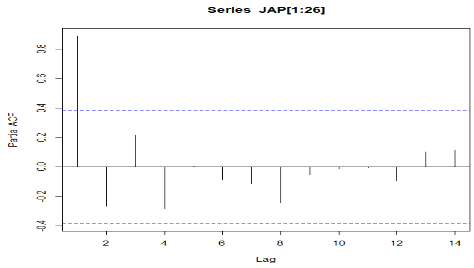
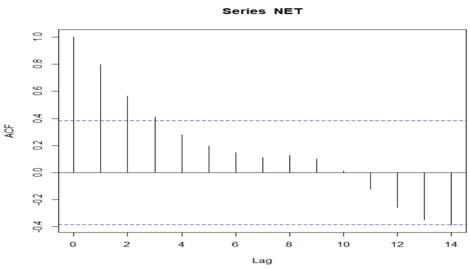
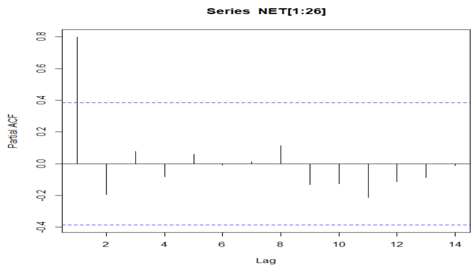
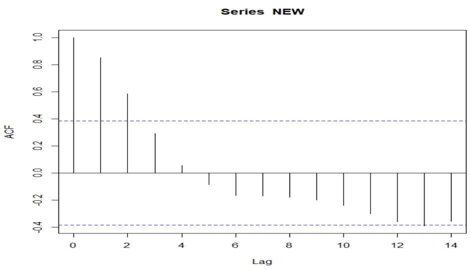
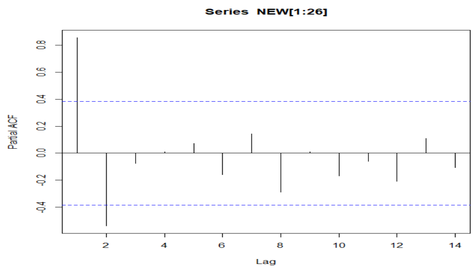
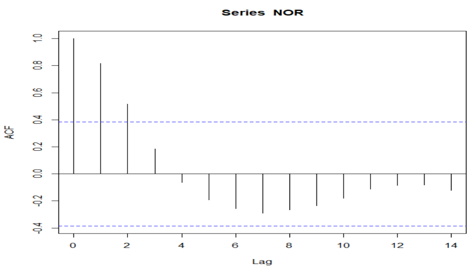
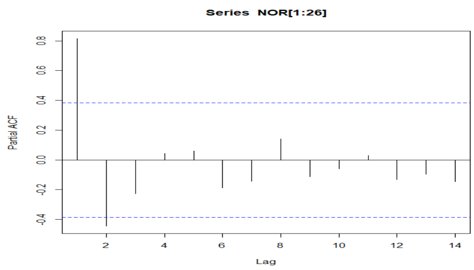
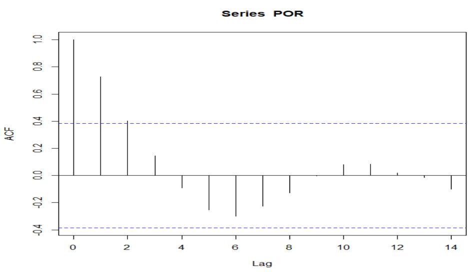
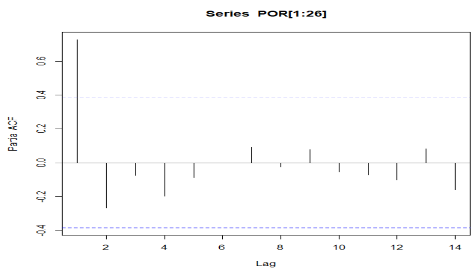
Country	ACF	PACF
Japan		
Netherlands		
New Zealand		
Norway		
Portugal		

Table 10: ACF and PACF for the last five countries

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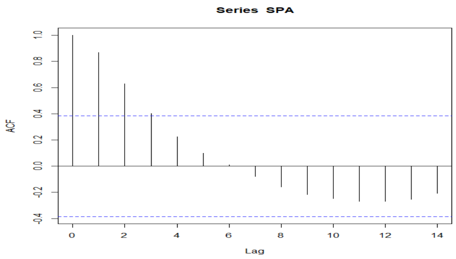
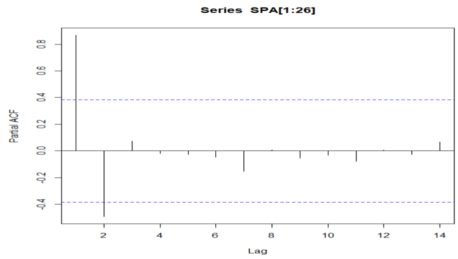
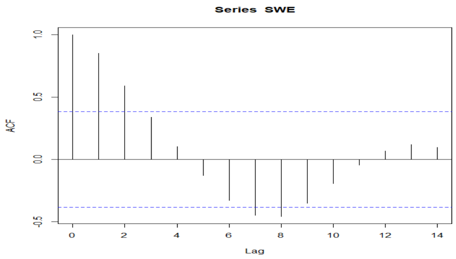
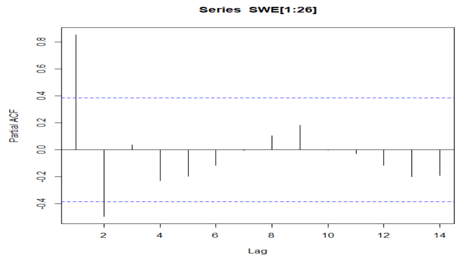
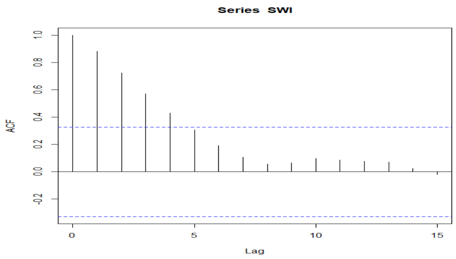
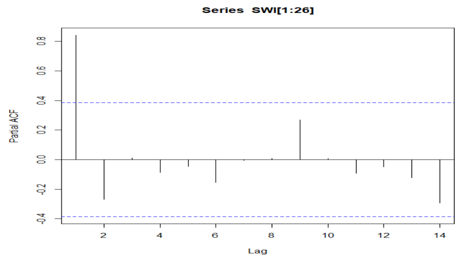
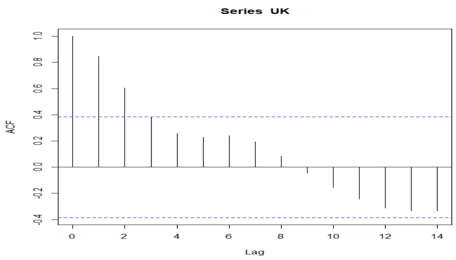
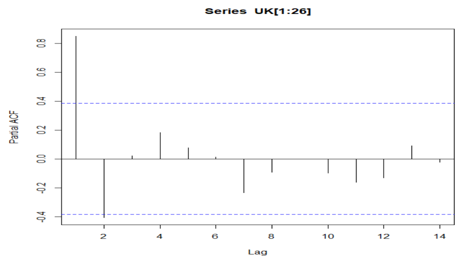
Spain		
Sweden		
Switzerland		
United Kingdom		
United States