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G7 Countries Unemployment Rate Predictions Using Seasonal Arima-Garch Coupled Models

G7 Ülkeleri İşsizlik Oranı Tahminleri: SARIMA-GARCH Model Karşılaştırması

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Öz: İşsizlik verilerinin yakın zamanda mevsimsellikten arındırılmış olarak yayınlanmış olmasına rağmen, mevsimsellik hareketli ortalama (MA) veya oto-regresif (AR) terimlerde hala var olabilir. Bu, oto-korelasyon fonksiyonu (ACF) ve kısmi ACF (PACF) diyagramlarında düzenli bir model arayarak tespit edilebilir. Bu nedenle, işsizlik oranlarını tahmin etmeyi amaçlayan modeller, daha iyi ortalama denklem tahminleri elde etmek için mevsimsellik özelliklerini dikkate almalıdır. Tek değişkenli modeller çoğunlukla entegre ARMA (ARIMA) veya genelleştirilmiş oto-regresif heteroskedastik (GARCH) modelleri veya bunların herhangi bir kombinasyonunu kullanır. Ortalama denklemler daha iyi yapılandırıldıktan sonra, GARCH varyans denklemi tahminlerinin tahminlerde daha doğru sonuçlar vermesi beklenir. Bu çalışmada ilk olarak, 1995-2019 dönemi için G-7 ülkelerindeki mevsimsellikten arındırılmış işsizlik oranı verilerinin ACF'leri ve PACF'leri incelenmektedir. Daha sonra, GARCH'ın mevsimsel ARIMA (SARIMA) bağlı oynaklık modellerinin ortalama, mutlak değer GARCH, GJR-GARCH, üstel GARCH ve asimetrik GARCH modellerinin 4 çeyrek ve 8 çeyrek ileriye dönük tahmin performansını karşılaştırır. Bu modellerin performansı da SARIMA ve MA filtreli volatilite modelleriyle karşılaştırılmıştır. Sonuçlar, mevsimselliğin mevsimsellikten arındırılmış işsizlik verilerinde bile yeniden incelenmesi gerektiğini göstermektedir, çünkü SARIMA modelleri örneklem dışı tahmin hataları açısından ARIMA modellerinden daha iyi performans göstermektedir. SARIMA-GARCH modellerinin yanı sıra daha iyi örneklem dışı tahmin doğruluğu sağlar.

Anahtar Kelimeler: Mevsimsellik, İşsizlik, SARIMA, GARCH, Tahmin

JEL Sınıflandırması: E24, C22, C52

Abstract: Despite the unemployment data have been recently released as seasonally adjusted, seasonality may still exist in moving average (MA) or auto-regressive (AR) terms. This can be detected by searching for a regular pattern in auto-correlation function (ACF) and partial ACF (PACF) diagrams. Therefore, models that aim to forecast unemployment rates should consider their seasonal properties so as to obtain better mean equation estimations. Univariate models mostly employ integrated ARMA (ARIMA) or generalized auto regressive conditional heteroscedastic (GARCH) models or any combination of them. Once the mean equations are structured better, GARCH estimations of variance equation is expected to perform better accuracy in forecasts. This study first examines the ACF's and PACF's of seasonally adjusted unemployment rate data in G-7 countries for 1995-2019 period. Then it compares the 4-quarter and 8-quarter ahead forecast performance of the seasonal ARIMA (SARIMA) coupled volatility models of GARCH in mean, absolute value GARCH, GJR-GARCH, exponential GARCH and asymmetric GARCH models. The performance of these models is also compared to SARIMA and MA filtered volatility models. The results show that seasonality should be re-examined even in seasonally adjusted unemployment data, since SARIMA models outperform ARIMA models in terms of out of sample forecast errors. Besides SARIMA-GARCH models provide better out of sample prediction accuracy.

Keywords: Seasonality, Unemployment, SARIMA, GARCH, Forecast

JEL Classification: E24, C22, C52

1. Introduction

Unemployment rates have undergone change among developed countries across the time. The relation between past and present years can clarify the fluctuations over time for each country.

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The model creation can offer assistance to dissect the unemployment rate and comparison will give chance to appropriate prediction. In this paper, the univariate models will be applied to predict the unemployment rates of G7 countries to interpret the changes over the time. Both ARIMA and GARCH models are proper due to the fact that the trend and seasonality are the issues of time series. ARIMA-GARCH modelling has moreover utilized to analyse various topics in different areas separated from unemployment rates such as inflation, gold price, electricity price, water demand, travel time and emergency care. The studies clarify how ARIMA and GARCH modelling are favourable.

Zhang et al. (2014) state that using GARCH model may be affected if there is a trend or seasonality, therefore they have used two component GARCH models that are able to model trend and seasonality of travel time data. The empirical sample include a freeway corridor in Houston, Texas and United States to test the proposed model, and Zhang et al. (2014) have claimed that it is also worth trying different variations of GARCH models to estimate the normalized residuals. Tan et al. (2010) proposes a model, which is creating a novel price forecasting method based on wavelet transform combined with ARIMA and GARCH models, is more accurate than the other price forecast methods to estimate electricity price based on wavelet transform.

Jones et al. (2002) have described a model that can forecast the daily number of occupied beds due to emergency admissions in an acute hospital. The authors highlighted that a period of high volatility, indicated by GARCH errors, will result in an increase in waiting times in the Accident and Emergency(A&E) Department. They infer that forecasting bed occupancy and volatility will help in the scheduling of elective admissions. Nyoni (2018) has mentioned prediction of inflation rates in Kenya over the period 1960-2017 using both ARIMA and GARCH modelling approaches. The order determination has made based on Akaike and Theil’s U statistics. The authors’ conclusion indicates that annual inflation in Kenya is likely to continue rising. Another study about prediction of inflation rates is done for Nigeria over the period 1960- 2017 by using ARMA, ARIMA and GARCH models. Nyoni & Nathaniel (2018) have concluded inflation in Nigeria is likely to rise to about 17% per annum by end of 2021 and is likely to exceed that level by 2027.

Caiado (2009) has examined the daily water demand forecasting performance of double seasonal univariate time series models Holt-Winters, ARIMA, and GARCH based on multistep ahead forecast mean squared errors to investigate whether combining forecasts from different methods could improve forecast accuracy or not. Caiado (2009) says that combining forecast is more adequate for short term forecasting. According to Sigauke & Chikobvu

(2011), the daily peak electricity demand forecasting can be more convenient by using the Reg-SARIMA-GARCH model, which produces better forecast accuracy with a mean absolute percent error (MAPE).

Tran et al. (2015) investigate forecasting the traffic of mobile communication network operating in Vietnam. Arima model has been used to represent mean component while GARCH model has been used to represent its volatility. Crawford & Fratantoni (2003) have studied over house prices, and has used three types of univariate times series model: ARIMA, GARCH and Regime-Switching. The authors have concluded that Regime-switching model performs better in sample forecasting, while Arima models are better in out of sample forecasting.

In this paper, the univariate models are generated to forecast the unemployment rate of G7 countries by considering the changes over time and seasonality, and forecast accuracies are calculated to compare the adequateness of the used models. There are studies that forecast unemployment rate of a single country by using univariate models. However, this study has included seven countries: Canada, Japan, United States, Germany, Italy, United Kingdom and France. In addition to this, seasonality has been considered again for seasonality adjusted data to understand whether it is enough to explain seasonality or not. The quarterly seasonally adjusted data is used to forecast for the January 1955- June 2019 period. The data period differs for France, Germany, Italy and United Kingdom. The period is 2003-2019 for France, 1998-2019 for Italy, 1962- 2019 for Germany and 1999-2019 for United Kingdom. The Arima and Seasonal Arima models have obtained, and ARIMA-GARCH, SARIMA-GARCH and MA(0,1) filtered GARCH volatility models are used due to the fact that both seasonality and volatility have to be considered. The result of this study will help to understand how seasonality and heteroskedasticity of unemployment rate series of each country important to create more appropriate models.

2. Literature Review

The unemployment rates of G7 countries data have analysed and adequate models have created by using univariate models with in sample forecasting and it has tested with measures of forecast accuracies. There exists a considerable body of literature on forecasting unemployment rates with different countries such as Canada, Germany, US, UK, Japan, Romania and Nigeria. Khan Jaffur et Al. (2017) forecast the unemployment rate of Canada by using monthly seasonally adjusted unemployment rates for the 1980-2013 period. They test their out of sample forecasts with three measures, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The authors conclude with the models but the literature on analysis of unemployment rate is less consistent, because the interpretation about unemployment is not included.

Montgomery, Zarnowitz, Tsay & Tiao (1998) covered forecasting of quarterly US unemployment rate extensively. In addition to univariate models, multivariate models also included. Business cycle is considered and the comparison between monthly and quarterly data exists. Because it is old study it is not include broad period of data, A recent study by Proietti (2003) included after 1993 until December 2000. However, he just used monthly data to forecast. Forecast horizons and measures of forecast accuracies are different than previous study. There is another study that forecasting unemployment rate of Germany. Funke (1992) stated that unemployment remains a serious problem in most OECD countries and should contribute to the success of labour market policy decisions. He forecast the monthly German unemployment rates for the 1965- 1989 period. He used both univariate and multivariate models. After he checked the model by out of sample forecasting, MA (1) model is adequate to explain German unemployment rates based on the measure RMSE.

Another paper is about Nigeria unemployment rates. Nkwatoh (2012) claimed unemployment is one of the most challenging problems facing the governments of developing countries. Because the unemployment rates are very high in Nigeria, he forecast the unemployment rates with univariate models by using quarterly unemployment rates. In the model selection part RMSE, MAPE and MAE are used. All the measures give the same result as ARIMA (1,1,2)/ ARCH (1). Nevertheless, the paper has too much table that are unnecessary and it include just short run projection.

The forecasting unemployment rates of UK have also modelled by using ARIMA - GARCH models. The scope of the data is over the period January 1971 to December 2002. Floros (2005) stated that MA (4)-ARCH (1) provides superior forecasts of unemployment rate for total forecasting sample based on forecast accuracies (MAPE, MAE and RMSE). There are four sub period for out of sampling like the first sample include first 300 observation used to predict the parameters and the remain 84 observation has used for forecast evaluation. The empirical evidence derived from the investigation suggests a close relationship between forecasting theory and labour market conditions. There is another paper on forecasting UK unemployment rate by using GARCH, TAR and ANN models. Johnes (1999) have said that AR(4) model is dominated for monthly UK unemployment rates.

There are other studies to forecast the unemployment rates, but in the studies ARIMA and GARCH models are not preferred. The one study is forecasting Japan unemployment rates by using ARFIMA model. Kurita (2010) claimed that the preferred ARFIMA model is a satisfactory representation of the data and is useful as a forecasting device. Kurita (2010) concluded that ARFIMA model is more representative to explain the Japan's unemployment rates accordance with a RMSE and MAPE.

Simionescu (2013) investigate which institution make the most convenient forecast for Romania by comparing accuracies with RMSE, MAE and Theil's U methods. Accordance with the paper, the most appropriate predictions for the unemployment rate on the forecasting horizon 2001-2012 were provided by the Institute for Economic Forecasting (IEF), and the other ones are European Commission and National Commission for Prognosis (NCP). Therefore, the three institutions are compared. The best accuracy is provided by IEF, followed by EC and NCP (Simionescu, M.)

There is a study for re-examining the hysteresis hypothesis in unemployment for G7 countries over the period January 1992 to September 2008. Chang & Lee (2011) has said that the hysteresis in unemployment is approved for three countries: France, Germany and Italy when threshold unit root test is applied. Because the unit root hypothesis cannot be rejected for the time series with the period 1992-2008 and for the first difference, the authors has gone forward with TAR model.

Various studies have also prepared with using different methodology to predict unemployment rates. Gustavsson & Österholm (2010) search the relevance of unemployment hysteresis in seventeen countries that are OECD members, and they have concluded that there cannot be accurate support for a mean reverting unemployment rate be found for any country. They also claimed that hysteresis does not affect the UK and US.

Moshiri & Brown (2004) have modelled unemployment rate non-linearly, since linear models are not appropriate to explain asymmetric time series like unemployment data. According to Moshiri & Brown (2004), a solution can be found for solving asymmetric business cycle in the unemployment series by applying Artificial neural network models (ANN). Askitas & Zimmermann (2009) have investigated that innovative method to predict unemployment rates, which is using keywords searches. They have asserted that there is strong correlation between monthly unemployment rates of Germany and keyword searches.

Besides D'Amuri and Marcucci (2010) find out that there is a correlation between Google index and the unemployment rates, and it is statistically significant and strong. D'Amuri (2009) explains the relation between internet job search query and unemployment rates. He has investigated the case of Italy in short run by using weekly data. Fondeur & Karamé (2013) examine the forecast of France youth unemployment rates by using Google queries. The papers prove the strong correlation and give improved models. After these studies, Xu et al. (2013) has developed a set of data mining tools including neural networks (NNs) and support vector regressions (SVRs) to forecast unemployment trend. The authors conclude that some other Web information, including Web content information and Web link information, can be used to improve the forecast performance.

Milas & Rothman (2008) have used smooth transition vector error correction models (STVECMs) to forecast the unemployment rates of the four non-Euro G-7 countries, the U.S., U.K., Canada, and Japan. The authors have claimed that that no individual approach tends to outperform the others. Barnichon et al. (2012) estimate a forecasting model of unemployment based on labour force flows data. Datta, Lahiri et al. (1999) have proposed a hierarchical Bayes (HB) method using an unemployment time series generalization of a widely used cross-sectional model in small-area estimation. They suggest that their proposed model that combines both the cross-sectional and time series data performs the best.

3. Unemployment Data

In this research, unemployment rates of G7 countries will be modelled by using ARIMA-GARCH models. G7 consists seven major developed countries that are the largest IMF-advanced economies in the world. Therefore, which model can explain better in changes of unemployment rate of largest economies has been discussed in this study. The quarterly unemployment rates data have been used that is taken from World Bank. Data range determined between 1/1/1955 – 1/6/2019.

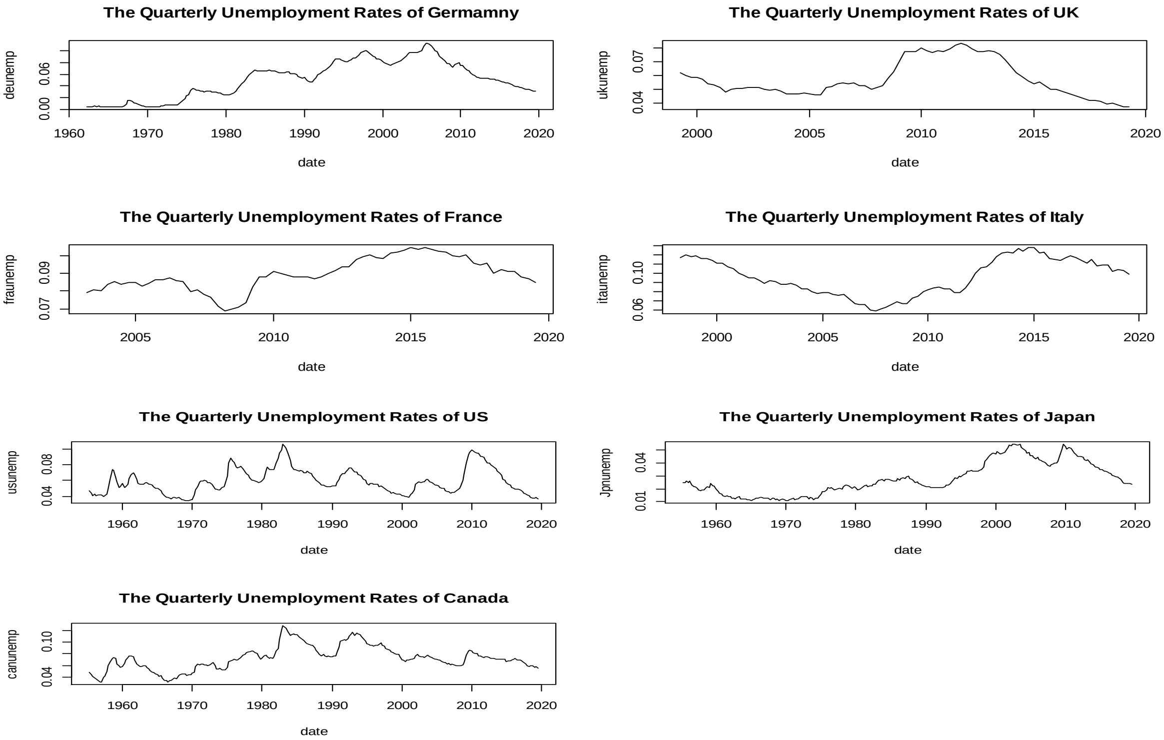


Figure 1. Quarterly rates of unemployment for G7 countries: "Graphs include data from January 1955 to June 2019 for The United States (US), Japan and Canada; from January 1962 to June 2019 for Germany; from January 1998 to June 2019 for Italy, from April 1999 to June 2019 for United Kingdom (UK) and from January 2003 to June 2019 for France."
Source: World Bank, 2020

Figure 1 depicts the historical development of the G7 countries unemployment rates. As it is seen unemployment rates in G7 countries tend to decrease after the global financial crisis hit the world in 2008 and 2009. However, Italy and France have experienced higher rates of unemployment even after 2010 till 2015. This fact coincides with euro area debt crisis of some member countries. On the other hand, The US unemployment shows very long-term cycles rather than trends. Germany's unemployment had an increasing trend after the re-unification of the west and east Germany till the 2005 elections. Germany performs very successful against unemployment during the Merkel era, even its decreasing trend couldn't be disrupted permanently by the global financial crisis in 2008.

Table 1. Summary statistics of G7 countries' unemployment data

	Canada	France	Germany	Italy	Japan	UK	US
#Observation	258	66	230	86	258	81	258
Observation Period	01/1955 06/2019	01/2003 06/2019	01/1962 06/2019	01/1998 06/2019	01/1955 06/2019	04/1999 06/2019	01/1955 06/2019
Minimum	3.03%	6.85%	0.37%	5.87%	1.07%	3.73%	3.40%
Maximum	12.93%	10.48%	11.35%	12.84%	5.43%	8.33%	10.67%
Mean	7.25%	8.93%	5.11%	9.62%	2.74%	5.73%	5.91%
Std Deviation	0.0206	0.0092	0.0315	0.0198	0.0124	0.0130	0.0159
Skewness	0.3670	-0.1807	-0.0369	-0.1428	0.5663	0.6297	0.7373
Kurtosis	-0.0334	-0.5703	-1.1674	-1.2802	-0.7971	-0.9057	0.0444
Jargue-Bera	5.8590	1.0498	12.75**	5.8085	20.48 ***	8.0116	23.7015
Q(10)	1671***	324***	2020***	573***	2369***	450***	1203***
Q(20)	2261***	359***	3413***	639***	4152***	518***	1250***

Notes: Significance at the 5% and 1% level is given respectively by **, ***. Jargue-Bera is the χ^2 statistic for test of normality. Q(10) and Q(20) are the statistics for Box-Ljung to check serial correlation.

Table 1 illustrates that Canada, Japan and US have 258 observation meaning that the data range is 1955-2019. Data has begun at future dates for other countries thus, the number of observations is less than 258. Germany has the lowest unemployment rate while Canada has reached the highest rate over the time. However, unemployment rate of Japan has the lowest mean, and the mean of Italy's unemployment is the highest. The unemployment rate is Japan is normally distributed at a level of 1 percent significance while the distribution of Germany unemployment rate is normal 5 percent level of significance based on Jargue-Bera test. The other countries' unemployment rates have not normally distributed. There is no time series that has serial correlation at 1 percent level of significance.

4. Methodology

A general ARMA model of unemployment u can be formed in a combination of auto-regressive and moving average terms as below;

$$u_t = a_0 + \sum_{i=1}^{m} a_i u_{t-i} + e_t - \sum_{i=1}^{n} f_i e_{t-i} \text{ where } m,n \geq 1 \text{ and } e_t \sim N(0,s_e^2) \quad (1)$$

where simple AR and MA models are special cases of the equation (1). If m=0 and n=0 U(t) turns into simple MA and AR models, respectively. Equation (1) can be also written in the form of AR and MA polynomials by using lag operator, L, as below:

$$Lu_t = u_{t-1} \text{ and } L^s u_t = u_{t-s}$$

$$(1 - a_1 L - a_2 L^2 \ldots\ldots - a_m L^m) u_t = a_0 + (1 - f_1 L - f_2 L^2 - \ldots\ldots - f_n L^n) e_t \quad (2)$$

The number of AR and MA coefficients in equations 1 and 2, m and n, indicates the order of ARMA model, thus it is an ARMA(m,n) model. If all characteristic roots of AR polynomial of ARMA(m,n) model, which is the left hand side of the equation (2), are inside the unit circle, then ARMA(m,n) model becomes weakly stationary. Otherwise, when there is 1 as a characteristic root, ARMA(m,n) model turns to be a unit root non-stationary. This model can be converted into a stationary model by differencing method. Once ARMA(m,n) model has been differenced model can be defined as AR integrated MA or ARIMA(m,k,n) model. The polynomial representation of ARIMA (m,k,n) model ca n be written as below

$$(1 - a_1 L - a_2 L^2 \ldots\ldots - a_m L^m)(1 - L)^k u_t = a_0 + (1 - f_1 L - f_2 L^2 - \ldots\ldots - f_n L^n) e_t \quad (3)$$

where k shows the order of integration or number of differencing. Most of financial and economic time series follow a non-stationary process. The order of differencing can be decided by applying unit-root tests such as augmented Dickey-Fuller (ADF) or Philips-Perron test (Said and Dickey, 1984; Phillips and Perron, 1988)

On the other hand, the order of MA and AR coefficients can be determined by examining the pacf and acf and their plots or other analytical methods (Tsay and Tiao, 1984). Once the model has been constructed, its adequacy can be tested by a Portmanteau test of autocorrelation proposed by Ljung and Box (1978), which is a modified version of Box and Pierce (1970) test of auto-correlation.

$$Q(z) = T(T+2) \sum_{l=1}^{z} \frac{\tilde{P}^2}{T-l} \quad (4)$$

where z is the maximum number of lags identified by information criteria, T denotes number of observations, l is the number of lags and P denotes the autocorrelation. Equation (4) provides the statistics of chi-squared test of null of no serial-correlation.

Seasonality is a very common feature of financial and economic time series, while most of the data announced publicly is seasonally adjusted that the seasonal patterns are already removed from the original data. Seasonal patterns are repeating data specifications in a specific frequency, such as higher inflation in 1st quarters and lower unemployment in 4th quarters. Seasonality should be considered to obtain more robust forecasts and analysis. Seasonal differencing might not be sometimes sufficient to handle the seasonal pattern of the time series, thus in addition to ordinary seasonal differencing, seasonality in MA and AR should be analysed.

$$(1 - L^d)(1 - L) u_t = (1 - fL - fL^{sma}) e_t \quad (5)$$

In equation (5), "d" represents seasonal differencing period and "sma" represents the seasonal period in MA polynomial. The model in equation (5) can also be extended into a multiplicative representation as well as seasonality in AR polynomial. Seasonal ARIMA (SARIMA) models are structured as (m,k,n)X(r,d,s) period number. m, n and k denote auto-regressive, regular integration and moving average orders, respectively. r,d,and s denote seasonal auto-regressive, seasonal integration and seasonal moving average orders, respectively.

After a mean equation specified by ARIMA and/or SARIMA models, even though the residuals of the model are serially uncorrelated, the square of residuals might be correlated. This problem might arise because of the time-varying volatility or heteroscedasticity. Therefore, one might model the volatility or residuals as well as the mean equation. The conditional mean equation of unemployment is as below,

$$u_t = E(u_t / I_{t-1}) + \varepsilon_t \ \textit{and} \ \varepsilon_t = \sigma_t a_t \ \textit{where} \ a_t \sim N(0,1)$$
$$\rho_t = E(u_t / I_{t-1}); \textit{conditional mean of } u_t \tag{6}$$

where ε_t denotes error term and σ_t^2 denotes its variance, and I_{t-1} is the available information set at time t-1.

$$\varepsilon_t = u_t - \rho_t \ \textit{and} \quad \sigma_t^2 = \beta_0 + \sum_{i=1}^{h} \beta_i \varepsilon_{t-i}^2 + \sum_{j=1}^{g} \beta_j \sigma_{t-j}^2 \tag{7}$$

Equation (7) represents General Auto Regressive Conditional Heteroscedastic GARCH(h,g) model of the unemployment's mean equation error term. Equation (7) is Bollerslev's (1986) generalized form of original ARCH model proposed by Engle (1982). ARCH effects can be detected by an ordinary Ljung-Box test of serial-correlation to ε_t^2 series.

Nelson (1991) proposed exponential GARCH (e-GARCH) model to control the negative and positive values of financial time series. The model can be formulized as below;

$$\log(\sigma_t^2) = \beta_0 + \sum_{i=1}^{h} \left(\beta_i \varepsilon_{t-i} + \gamma_i \left(\left|\varepsilon_{t-i}\right| - E\left|\varepsilon_{t-i}\right|\right)\right) + \sum_{j=1}^{g} \beta_j \log(\sigma_{t-j}^2) \tag{8}$$

where β_i *and* γ_i control the sign and the size effects, respectively. Glosten et al. (1993) extended the e-Garch model to capture the positive and negative shocks asymmetrically by inserting an indicator function H, instead of relying on an expectations function over absolute and logarithmic values of the error term. The model is called as GJR-GARCH as detailed below;

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{h} (\beta_i \varepsilon_{t-i}^2 + \omega_i H_{t-i} \varepsilon_{t-i}^2) \sum_{j=1}^{g} b_j \sigma_{t-j}^2 , \ where \ \ 0 < H_t < 1 \qquad (9)$$

where the existence of indicator function H increases the importance of the asymmetry in conditional distribution in the persistence of the model. The other volatility model estimated in this study is Asymmetric Power GARCH (APARCH), which is proposed by Ding et al. (1993). APARCH model is a generalized type of model e-GARCH, GJR-GARCH and some other non-linear GARCH models. APARCH model

$$\sigma_t^\psi = \beta_0 + \sum_{i=1}^{h} b_i \left(\left| \varepsilon_{t-i} \right| - \gamma_i \varepsilon_{t-i} \right)^\psi + \sum_{j=1}^{g} b_j \log(\sigma_{t-j}^\psi), \qquad \psi \in \mathbb{R}^+ \qquad (10)$$

If $\psi = 2 \ and \ \gamma = 0$ APARCH turns into simple GARCH model, and if $\psi = 2$, it converges to GJR-GARCH model.

This study evaluates the forecast accuracy of the ARIMA, SARIMA and volatility models of unemployment data in G7 countries by employing mean absolute percentage error (MAPE) and root mean square error values.

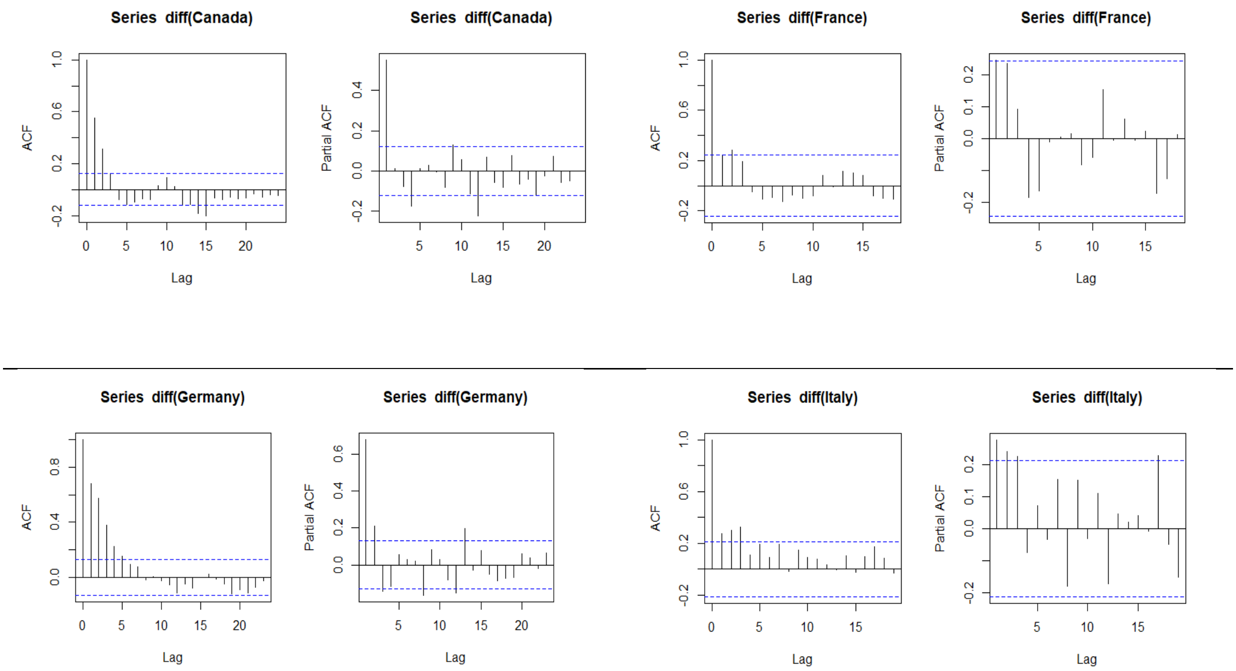
$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_i - x_i}{y_i} \right| \qquad \qquad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \qquad (11)$$

where y_i is the actual value, x_i is the forecast value, and n is the sample size. Makridakis (1993) has explained that accuracy measures, error statistics or measures, and loss functions are alternative ways of getting information about the ability of a forecasting method to predict actual data, either out of sample or in sample forecasting.

5. Estimation, Results and Discussion

Unemployment rate of G7 countries has been analysed by using univariate models. Logarithmic series have been used, and stationarity has been checked before beginning the analysis. The first step of analyse has been checking stationarity with Augmented Dickey Fuller test. Integration level is 2 for United Kingdom and 1 for the remains. The series are non-stationary based on Augmented Dickey Fuller test. Because all series include integration level ARIMA model has been created. ARIMA orders has been determined by autocorrelation function and partial autocorrelation function. AR order (p) has been determined based on autocorrelation function while MA order (q) has been determined based on partial autocorrelation function.

Figure 2 demonstrates correlograms of series. First two graphs prove that AR order (p) is 2 and MA order (q) is 0 for Canada. But second order of autoregression has not significant in the model, therefore it has been eliminated, as a conclusion ARIMA (1,1,0) model has been generated. For France data, there is no MA order, and AR order is 2 at the beginning, however second coefficient has been eliminated due to the fact that it has not significant. ARIMA (1,1,0) model has been created for France. When the second graph of second row of Figure 2 has been checked AR order 4 and MA order is 2 for Germany. After the elimination of insignificant coefficients ARIMA (1,1,2) model has been obtained at the end. For Italy AR order has been determined as 3 and MA order has been determined as 2. ARIMA (1,1,1) has been selected to explain Italy unemployment rate. Unemployment rate of Japan can be explained with ARIMA (3,1,1) model accordance with autocorrelation and partial autocorrelation functions. Correlograms of UK illustrates that both AR and MA orders are 1. Insignificant coefficients have occurred. There have been two ways to eliminate; elimination of MA order and obtaining ARIMA (1,2,0) or elimination of AR order and getting ARIMA (0,2,1) model. Based on the Akaike Information Criteria ARIMA (0,2,1) performs better. Lastly, ARIMA (2,1,0) model can be generated for United States, but coefficient of second parameter has insignificant. Thus, ARIMA (1,1,0) has been created to clarify unemployment rate of the US.



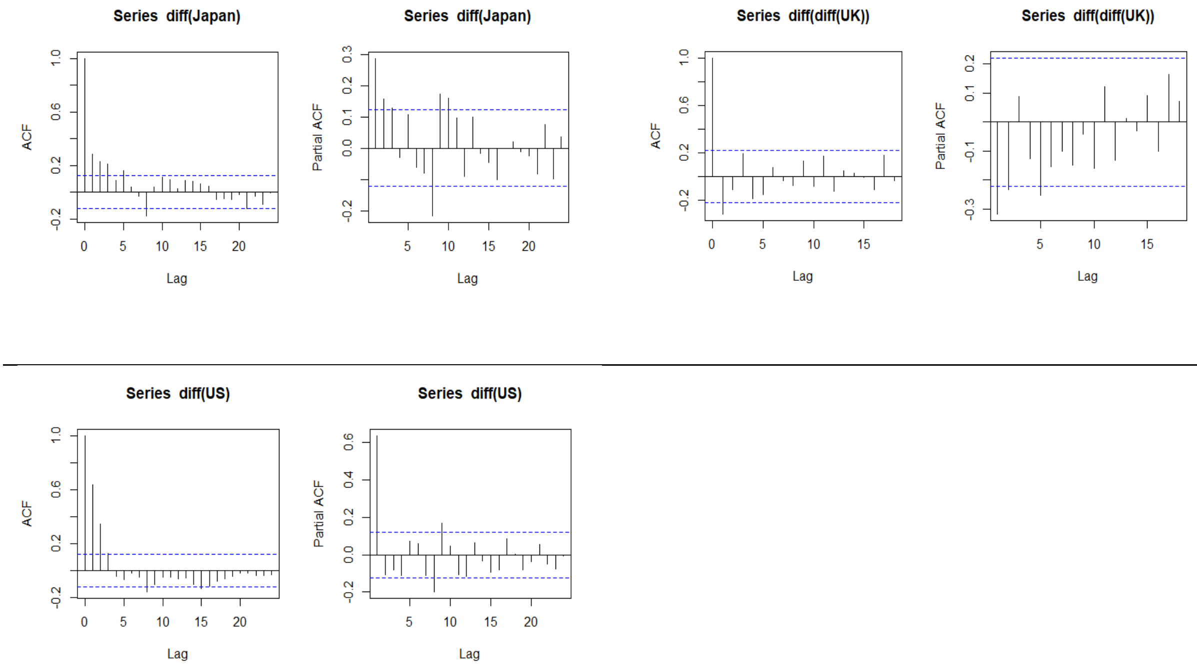


Figure 2. Correlograms of unemployment rates of G7 countries: “Correlograms include determined integration level that is 2 for UK and 1 for other countries.

Table 2 presents the estimated coefficients of the ARIMA parameters. ARIMA model cannot be enough to explain unemployment rates. Although seasonally adjusted data have been used, seasonality have been checked. Seasonality effect should be removed before modelling. There is no seasonal effect of Italy and France. There has been still seasonality effect for other countries in spite of seasonally adjusted data. Table A.1 illustrates SARIMA orders and coefficients of parameters in appendix.

Table 2. Seasonal Arima Parameter Estimations

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*USA*
I(d)	1	1	1	1	1	2	1
Ar1	0,53852 (0.0538)	0,29498 (0.1191)	0,61989 (0.05962)	0,8201 (0.1265)	0,72067 (0.13012)		0,6659 (0.04844)
Ar3					0.15196 (0.08102)		
Ma1				0,5768 (0.1780)	0,55879 (0.14044)	0,57802 (0.09324)	
Ma2			-0,24769 (0,07193)				
Sar1	0.53276 (0.1115)		0,68307 (0,06134)		0,3852 (0.11235)		0.53120 (0.08021)
Sma1	0,77641 (0,09179)		0,8336 (0,03276)		0,70241 (0.09231)	0,3274 (0.10765)	0,86275 (0.05185)
Arch	58.519**	12.4	282.64**	23.30	124.70**	13.53	69.29**

*Effect Test**							
Durbin Watson	2,0715	2,1128	1,9818	1,9837	1,9812	1,9523	1,9724

**Chi-squared test of auto-correlation in error term. Significance level at %1 given by* **. Notes: Standart deviations of the estimations are in parenthesis ( ). Seasonal arima models are structured as (m,k,n)X(r,d,s) period number. m, k and n denote auto-regressive, integration and moving average orders, respectively. r,d,and s denote seasonal auto-regressive, seasonal integration and seasonal moving average orders, respectively. Period number states the consecutive seasonal order. Model Summary: *Canada: (1,1,0)X(1,0,1)4; Japan: (3,1,1)X(1,0,1)4; France: (1,1,0)X(0,0,0)4*; *UK: (0,2,1)X(0,0,1)4; Germany: (1,1,2)X(1,0,1)4; USA: (1,1,0)X(1,0,1)4*; *Italy: (1,1,1)X(0,0,0)4.*

Autoregressive Conditional Heteroskedasticity, or ARCH, is a method that models the change in variance over time in a time series. Therefore, we can create better model by modelling volatility. Time series have to be checked whether arch effect exists or not. Table 2 shows that France, Italy and UK have not ARCH effect. Thus, ARCH and GARCH models have been generated for Canada, Germany, Japan and US.

Table 3. 4 quarters (1 year) ahead forecast accuracy results

		Canada		Germany		Japan		United States	
	Garch Model	*MAPE*	*RMSE*	*MAPE*	*RMSE*	*MAPE*	*RMSE*	*MAPE*	*RMSE*
ARIMA	-	0,05275	0,00336	0,06543	0,00233	0,01175	*0,00032*	0,01779	0,00090
SARIMA	-	0,06448	0,00413	0,08808	0,00316	0,01364	0,00039	0,02614	0,00173
MA(0,1) Filtered-GARCH	sGarch	0,04903	0,00311	0,07875	0,00271	0,00764	0,00034	0,01810	0,00096
	eGarch	0,04942	0,00313	0,07858	0,00271	*0,00738*	0,00034	0,01964	0,00101
	gjr-Garch	0,04912	0,00312	0,07874	0,00271	0,00758	0,00034	0,01901	0,00099
	Aparch	*0,04890*	*0,00310*	0,07862	0,00271	0,00773	0,00034	0,01899	0,00099
Sarima Fixed Garch	sGarch	0,05483	0,00350	*0,06489*	*0,00230*	0,05600	0,00144	0,08865	0,00342
Arima-Garch	sGarch	0,05144	0,00328	0,06582	0,00236	0,03502	0,00090	0,01797	0,00093
	eGarch	0,05044	0,00323	0,07059	0,00254	0,03377	0,00089	*0,01778*	*0,00087*
	gjr-Garch	0,05174	0,00330	0,06604	0,00236	0,03948	0,00101	0,01779	0,00089
	Aparch	0,05166	0,00330	0,06604	0,00236	0,03083	0,00080	0,01779	0,00089

Quarterly unemployment rates of G7 countries have been analysed to understand which model is more appropriate. ARIMA, SARIMA, MA(0,1) Filtered GARCH and derivations of Garch models have been generated. The coefficients have been adequate; therefore, using out of sample forecast results can compare models. Since data is quarterly, four-quarters (1 year) and eight-quarters (2-years) ahead forecasts have been compared.

As Table 3 demonstrates, in 1 year horizon, SARIMA-GARCH model performs better then non seasonal models only in Germany unemployment forecasts. On the other hand, GARCH coupled mean models (MA(0,1) filtered GARCH and ARIMA-GARCH) performs better forecast accuracy in remaining countries. According to MAPE estimations of 1 year ahead forecasts, GARCH coupled models outperform conventional SARIMA and ARIMA forecasts of the unemployment data.

Table 4 illustrates the 2-year ahead forecast performance results of regarding models of unemployment data. SARIMA-GARCH models better perform in Canada, Japan and The US unemployment data, although non-seasonal models have better performance in 1-year data of same countries. On the other hand, ARIMA-GARCH model predicts better in Germany unemployment data in 2-year horizon. Based on MAPE and RMSE, the GARCH coupled mean models perform better in longer horizon and seasonal models' predictions are more successful except Germany unemployment data in 2-year horizon.

Table 4. 8 quarters (2 year) ahead forecast accuracy results

		Canada		Germany		Japan		United States	
	Garch Model	*MAPE*	*RMSE*	*MAPE*	*RMSE*	*MAPE*	*RMSE*	*MAPE*	*RMSE*
ARIMA	-	0,07105	0,00440	0,08346	0,00319	0,15773	0,00410	0,04273	0,00201
SARIMA	-	0,07957	0,00513	0,12632	0,00488	0,14579	0,00378	0,13962	0,00635
MA(0,1) Filtered-GARCH	sGarch	0,09565	0,00584	0,09565	0,00369	0,16272	0,00422	0,09067	0,00396
	eGarch	0,09547	0,00583	0,09597	0,00370	0,16263	0,00422	0,09231	0,00403
	gjr-Garch	0,09558	0,00584	0,09545	0,00368	0,16268	0,00422	0,09157	0,00400
	Aparch	0,09571	0,00584	0,09589	0,00370	0,16282	0,00422	0,09150	0,00400
Sarima Fixed Garch	sGarch	*0,06934*	*0,00430*	0,07718	0,00297	*0,10075*	*0,00263*	*0,03789*	*0,00181*
Arima-Garch	sGarch	0,07563	0,00467	0,07428	0,00284	0,13420	0,00349	0,04031	0,00191
	eGarch	0,07858	0,00484	*0,02174*	*0,00079*	0,17256	0,00445	0,04584	0,00213
	gjr-Garch	0,07469	0,00461	0,07119	0,00274	0,12753	0,00331	0,04399	0,00206
	Aparch	0,07456	0,00460	0,07118	0,00273	0,12616	0,00328	0,04400	0,00206

There is no ARCH effect in UK unemployment rate mean equation residuals; therefore, only ARIMA and SARIMA models have been generated. Table 5 shows that UK's unemployment data is better forecasted by ARIMA model than SARIMA model in 1-year horizon, on the contrary SARIMA model performs better than ARIMA model in 2-year ahead forecast horizon.

Table 5. The United Kingdom unemployment rate forecast error accuracy results

	4 quarters ahead	8 quarters ahead

	MAPE	*RMSE*	*MAPE*	*RMSE*
Arima fixed	*0,047123178*	*0,001888799*	0,045377511	0,002034573
Sarima fixed	0,051545824	0,002032444	*0,03798133*	*0,001720763*

The outperforming forecast accuracies from mean and volatility equation estimations of ARIMA, SARIMA and SARIMA-GARCH models show that (i) seasonality may still occur in seasonally adjusted data, (ii) volatility tests are required in univariate time series modelling, and (iii) univariate models' prediction power varies respect to its forecast horizon. Firstly, seasonality should be checked in univariate data, due to the fact that researchers are most likely to analyse data intervals that probably don't coincide with the original or complete observation period. The seasonal structure in estimations may alter with respect to the estimation period included into the research. On the other hand, this modification is expected to happen in seasonal MA and AR parameters rather than seasonal differencing parameters.

Secondly, the presence of conditional variance should be considered especially in economic and financial times series. Therefore, this study checks for the ARCH effects in the residuals of the estimated seasonal mean equations. Table-2 shows that 4 out of G-7 countries unemployment data contain autocorrelation in their squared residuals and Tables 3-4 imply that volatility models of unemployment data have better forecast accuracy. This suggests that mean-variance modelling of economic time series might provide more efficient parameter estimations and more powerful predictions (Tsay, pp.110, 2005). Lastly, researchers commonly initiate prediction power, as a decision rule, to determine the rate of success among the different univariate models of a single time series. However, the prediction accuracy may propose different mean-variance models for the same time series within different forecast horizons. For instance; in Table-3 and Table-4, forecast accuracy measures, MAPE and RMSE, do suggest different mean-variance models, which don't overlap in 4 quarters and 8 quarters ahead forecasts. Hence model selection process should either compare prediction powers in different forecast horizons or indicate whether the model is appropriate for short- or long-term forecasts.

6. Conclusion

This study examines the forecast accuracy performance of seasonally adjusted unemployment rate data of G7 countries. It measures the forecast error of univariate Arima and seasonal Arima models as well as same models coupled with GARCH volatility models. The unit root tests for the stationarity of the unemployment series suggest that all data is integrated with different orders. The acf and pacf figures of the post-integrated data have been illustrated so as to decide which ordinary and seasonal auto-regressive and moving-average orders to be selected with seasonal periods. Then, the parameter estimations of these Arima and seasonal Arima models have been presented. The results show that significant parameter estimation for seasonal parameters. However, MAPE and RMSE accuracy measures have been initiated to determine whether seasonal structuring of the unemployment data is necessary.

The forecast errors are calculated for 4-quarter and 8-quarter ahead forecast horizons. Although in 4-quarter ahead forecasts, some mixed results have been obtained, the garch-coupled models seem to perform better. In 8-quarter ahead forecast horizon, the seasonal models outperform non-seasonal models. The result is that seasonality should be considered even though data is structured seasonally adjusted (Tsay, pp.219, 2005). In this paper, the seasonality effect has been detected except France and Italy. Therefore, Italy and France are estimated within only ARIMA structure. Second, in shorter-forecast horizons ARIMA model explains better unemployment series, although SARIMA fixed GARCH is better in longer forecast horizon except for Germany. These results show that GARCH coupled mean models have higher forecast accuracy in both short and longer-term periods. Seasonal models become significantly successful respect to non-seasonal models in 2-year period ahead forecasts.

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Appendix

Table A-1. ARIMA (p,d,q) model parameter estimation results.

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*USA*
I(d)	1	1	1	1	1	2	1
Ar1	0.5193 (0.0538)	0.2950 (0.1185)	0.5737 (0.0592)	0.8198 (0.1291)	-0.7866 (0.0844)		0.6180 (0.0491)
Ar3					0.1319 (0.0556)		
Ma1				0.5764 (0.1864)	-0.8634 (0.0671)	0.5487 (0.1358)	
Ma2			-0.274 (0.0718)				

Model Summary: Canada: (1,1,0) - Japan: (3,1,1) - France: (1,1,0) - UK: (0,2,1) - Germany: (1,1,2) - USA: (1,1,0) - Italy: (1,1,1). Notes: Standart deviations of parameter estimations are in paranthesis ( ). p,d and q denote auto-regressive (Ar), difference (I(d)) and moving average (Ma) orders, respectively.

Table A-2. Seasonally filtered Garch model parameter estimations. (standart deviations)

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*USA*
mu	0.04978 (0.02303)	-	0.00400 (0.03050)	-	0.02467 (0.02964)	-	0.04977 (0.02808)
Ar1	0.60689 (0.06206)	-	0.65868 (0.06785)	-	0.68302 (0.24235)	-	0.64916 (0.05325)
Ar3		-		-	0.08327 (0.10790)	-	
Ma1		-		-	-0.49782 (0.24636)	-	
Ma2		-	0.43600 (0.08661)	-		-	
Omega	0.00049 (0.00015)	-	0.00007 (0.00003)	-	0.00005 (0.00005)	-	0.00030 (0.00014)
Alpha 1	0.61825 (0.15047)	-	0.38156 (0.10041)	-	0.09048 (0.05930)	-	0.24982 (0.08895)
Beta1	0.28232 (0.11137)	-	0.61744 (0.07304)	-	0.88069 (0.07847)	-	0.58725 (0.12399)