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

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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 are 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

JEL Codes: E24, C22

1. INTRODUCTION

Unemployment rates have undergone change among developed countries across the time. There are various reasons to explain the changes, however, the relationship between present and past years can clarify the changes over time for one country. 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 when 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, Haghani & Zeng (2014) have stated 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, Haghani & Zeng (2014) have claimed that it is also worth trying different variations of GARCH models to estimate the normalized residuals. Tan, Zhang, Wang & Xu (2010) have claimed the proposed 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, Joy & Pearson (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 have inferred 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 has indicated 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) of 1.42%. Yaziz, Azizan, Zakaria & Ahmad (2013) states that the models to forecast gold must reflect its structure and pattern because gold has been considered a safe return investment due to the fact that its characteristic to hedge against inflation. The paper expresses that there are previous studies that generalized autoregressive conditional heteroskedastic (GARCH) models are used in time series forecasting to handle volatility in the commodity data series including gold prices (Yaziz, Azizan, Zakaria & Ahmad). Thus, the authors have studied on hybridization of potential univariate time series, and have said that combination of Arima and GARCH is a novel. Tran, Ma, Hao & Trinh (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 (Tran et all.). Crawford & Fratantoni (2003) has 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 applied to forecast the unemployment rate of G7 countries by considering the changes over time and seasonality, and 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. Some periods do not exist 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 considered. The result of this study will help to understand how SARIMA-GARCH models explain unemployment rates.

2. LITERATURE REVIEW

There are some studies about forecasting unemployment rates. The studies include one country or not include GARCH model or they have used different forecasting methods. The similar forecast accuracy models have been applied to compare the created models to predict the unemployment like MAE, RMSE and MAPE.

The article is giving information about crude oil price dynamics. The study examines the usefulness of ARIMA and GARCH models to model and forecast the conditional mean and volatility of weekly crude oil spot prices in eleven international markets (Algeria, Canada, China, Dubai, Indonesia, Norway, Russia, S.Arabia, UK, US and Venezuela) over the 1/2/1997–10/3/2009 period (Mohammadi & Su, 2010). The paper adds new techniques the previous ones. It focuses on weekly data instead of monthly data, and both oil exporting and oil importing countries are included. The authors use 4 volatility model to evaluate the oil prices; Garch, Egarch, Aparch and Figarch. Thus, the purpose of the paper is re-examining the time series properties of crude oil prices by extending it in these three directions. The authors try to model conditional mean and conditional variance with univariate models. After they got the mean and variance equation, the models are tested by using forecast accuracy by using out of sample forecasting instead of using in sample forecasting. Root mean squared error (RMSE) and mean absolute error (MAE) are used to evaluate forecasts.

Finally, MA (1) model is more appropriate to explain weekly oil prices. As we expected most of the time series can be model with MA and AR model with the first order. But we have to check whether other models are more appropriate or not. Because the authors suspect conditional mean and conditional variance, they checked various ARCH models. But the MAE and RMSE give the result as MA (1). This paper enlightens the evaluation methods to write the paper about unemployment. My paper will be about explaining the unemployment rates of G7 countries over the 1/1/1955 – 1/6/2019 period. Quarterly data will be used. The methodology will be similar like creating model with univariate models and evaluate with forecast accuracies. However, I will also consider seasonality. The paper adds a new look to measures when it is compared with past studies. To demonstrate the inadequacy of many

measures of forecast accuracy, the authors has worked with three examples of real monthly stock returns data. (Hyndman & Koehler, 2006)

The unemployment rates of G7 countries data has analysed and adequate models are created by using univariate models with in sample forecasting and it is 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) forecasted the unemployment rate of Canada by using monthly seasonally adjusted unemployment rates for the 1980-2013 period. They tested 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 ended up 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 has 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 (Floros, C.). 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. According to Kurita (2010), using a class of long memory or fractionally- integrated time series models with the view to accounting for persistency in unemployment rates. ARFIMA model is more representative to explain the Japan's unemployment rates accordance with a RMSE and MAPE. (Kurita, 2010)

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. Gusyavsson & Österholm conclude that there cannot be accurate support for a mean reverting unemployment rate be

found for any country. The authors also claimed that hysteresis does not affect the UK and US. Moshiri & Brown (2004) have investigated can be modelled unemployment rate which is non-linear. Because linear models are not appropriate to explain asymmetric time series like unemployment. According to the paper, 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. There is another study that predict unemployment rates by using google search, but in this case US monthly unemployment rates have been examined. D'Amuri and Marcucci (2010) says that there is a correlation between Google index and the unemployment rates, and it is statistically significant and strong. D'Amuri (2009) has also written another paper that explain 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, Li, Cheng & Zheng (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.

There is a study on out of sample forecasting experiment for the unemployment rates of the four non-Euro G-7 countries, the U.S., U.K., Canada, and Japan. Milas & Rothman (2008) have used smooth transition vector error correction models (STVECMs). The authors have claimed that that no individual approach tends to outperform the others.

Other papers about prediction of unemployment rates also exists. For instance, Barnichon, Nekarda and et all. (2012) have examine a forecasting model of unemployment based on labour force flows data. Datta, Lahiri, Maiti & Lu (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 have achieved that their proposed model that combines both the cross-sectional and time series data performs the best. Hyndman & Koehler (2006) stated that they consider comparing forecast accuracy of four simple methods: historical mean, random walk, simple exponential and Holt's method. They compared both in sample and out of sample forecasting with these four methods. After the models are created,

they are tested with forecast accuracy that are MAPE and its derivatives, RMSE, GMRAE and MASE.

3. UNEMPLOYMENT DATA

In this research, unemployment rates of G7 countries will be modelled by using ARIMA-GARCH models. The quarterly unemployment rates data is taken from World Bank.
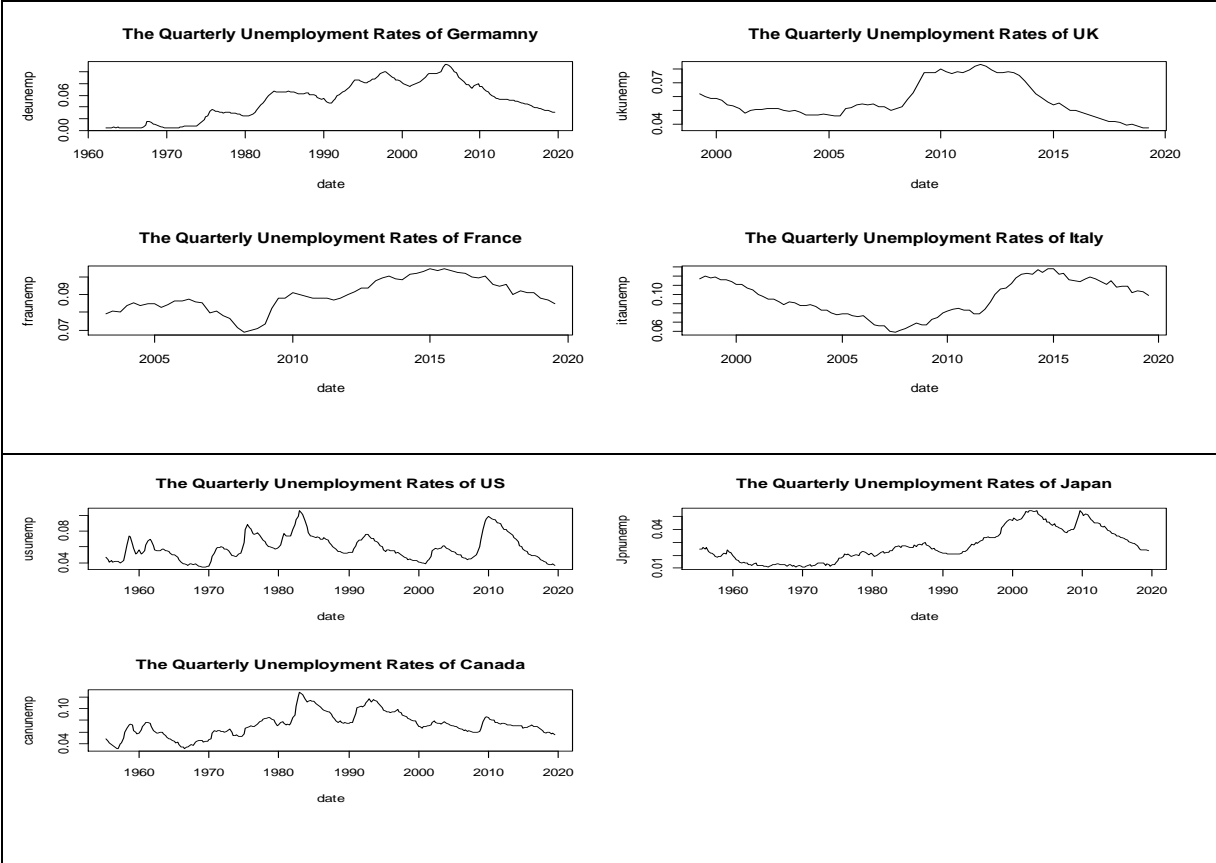

Figure 1: Quarterly rates of unemployment for G7 countries: "Graphs include data from January 1955 to June 2019 for The United States (US), Japan and Canada; from January 1962 to June 2019 for Germany; from January 1998 to June 2019 for Italy, from April 1999 to June 2019 for United Kingdom (UK) and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

Descriptive Statistics

	Canada	France	Germany	Italy	Japan	UK	US
Observation #	258	66	230	86	258	81	258
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***	324.2***	2020.8***	573***	2369***	450***	1203***
Q(20)	2261***	359.6***	3413.4***	639***	4152.1***	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. There are some missing values for other countries. Germany has the lowest unemployment rate while Canada has reached the highest rate. Japan has the lowest mean, and Italy has the highest mean. 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. There is no time series that has serial correlation at 1 percent level of significance.

4. METHODOLOGY

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. The four model has been created to forecast the unemployment, bretn oil prices, electricity prices and price level. To decide the best two model, all models should be compared with accuracy measures: mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean squared error (RMSE). R square can be checked also to see how strong the coefficients of models.

The calculations are as follows:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} = \frac{\sum_{i=1}^{n}|e_i|}{n}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right|$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

where y_i is the actual value, x_i is the forecast value, and n is the sample size.

5. ESTIMATION RESULTS

Unemployment rate of G7 countries has been analysed by using univariate models. 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. Logarithmic series has been used to create models. AR and MA order has been specified by using autocorrelation function and partial autocorrelation function. Figure A.1 illustrates ACF and PACF graph for each country in appendix. AR order is 3 for Japan, 0 for UK, and 1 for other countries and q is specified as 2 for Germany, 1 for Italy, Japan and UK, 0 for Canada, France and US. Table 2 demonstrates the 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)

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Sma1	0,77641 (0,09179)		0,8336 (0,03276)		0,70241 (0.09231)	0,3274 (0.10765)	0,86275 (0.05185)
Arch Effect Test*	58.519**	12.4	282.64**	23.30	124.70**	13.53	69.29**
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 (p,d,q)X(r,d,s) period number. p, d and q 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 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 hazve been generated. The coefficients have been adequate, therefore, models can be compared by using out of sample forecast results. The lowest forecast accuracies named as Mean Absolute Precentage Error (MAPE) and Root Mean Squared Error (RMSE) determine the best model. Because data is quarterly four-quarters and eight-quarters ahead forecasts have been compared.

In short run, MA(0,1) Filtered Aparch model is more appropriate, while SARIMA fixed GARCH explains better Canada as Table 3 demonstrates. Table 4 illustrate that both MAPE and RMSE shows that SARIMA Fixed GARCH explains unemployment rate of Germany in short run, ARIMA GARCH is better in long run. In the short run RMSE and MAPE results differs for Japan. MA(0,1) Filtered eGARCH is better to explain based on MAPE, while ARIMA interprets unemployment of Japan better based on RMSE. Table 4 also demonstrate that SARIMA Fixed GARCH is better option in the long run for Japan unemployment.

Table 4: 8 quarters ahead forecast accuracy results

	Garch Model	Canada		Germany		Japan		United States	
		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

Table 5: The United Kingdom unemployment rate forecast error accuary 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**

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 it is seasonally adjusted. 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. There is no ARCH effect in UK unemployment rate, therefore only ARIMA and SARIMA models have been generated, and ARIMA is better in shorter forecast horizon, despite SARIMA explains better UK unemployment in 8 quarters ahead forecasts.

References

Andrews, D. W., & Ploberger, W. (1996). Testing for serial correlation against an ARMA (1, 1) process. Journal of the American Statistical Association, 91(435), 1331-1342.

Askitas, N., & Zimmermann, K. F. (2009). Google econometrics and unemployment forecasting.

Barnichon, R., Nekarda, C. J., HATZIUS, J., STEHN, S. J., & PETRONGOLO, B. (2012). The Ins and Outs of Forecasting Unemployment: Using Labor Force Flows to Forecast the Labor Market [with Comments and Discussion]. Brookings Papers on Economic Activity, 83-131.

Caiado, J. (2009). Performance of combined double seasonal univariate time series models for forecasting water demand. Journal of Hydrologic Engineering, 15(3), 215-222.

Chang, T., & Lee, C. H. (2011). Hysteresis in unemployment for G-7 countries: Threshold unit root test. Romanian Journal of Economic Forecasting, 4, 5-14.

Crawford, G. W., & Fratantoni, M. C. (2003). Assessing the forecasting performance of regime-switching, ARIMA and GARCH models of house prices. Real Estate Economics, 31(2), 223-243.

D'Amuri, F. (2009). Predicting unemployment in short samples with internet job search query data.

D'Amuri, F., & Marcucci, J. (2010). 'Google it!'Forecasting the US unemployment rate with a Google job search index.

Datta, G. S., Lahiri, P., Maiti, T., & Lu, K. L. (1999). Hierarchical Bayes estimation of unemployment rates for the states of the US. Journal of the American Statistical Association, 94(448), 1074-1082.

Floros, C. (2005). Forecasting the UK unemployment rate: model comparisons. International Journal of Applied Econometrics and Quantitative Studies, 2(4), 57-72.

Fondeur, Y., & Karamé, F. (2013). Can Google data help predict French youth unemployment?. Economic Modelling, 30, 117-125.

Funke, M. (1992). Time-series forecasting of the German unemployment rate. Journal of Forecasting, 11(2), 111-125.

Gustavsson, M., & Österholm, P. (2010). The presence of unemployment hysteresis in the OECD: what can we learn from out-of-sample forecasts?. Empirical Economics, 38(3), 779-792.

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. International journal of forecasting, 22(4), 679-688.

Johnes, G. (1999). Forecasting unemployment. Applied Economics Letters, 6(9), 605-607.

Jones, S. A., Joy, M. P., & Pearson, J. O. N. (2002). Forecasting demand of emergency care. Health care management science, 5(4), 297-305.

Khan Jaffur, Z. R., Sookia, N. U. H., Nunkoo Gonpot, P., & Seetanah, B. (2017). Out-of-sample forecasting of the Canadian unemployment rates using univariate models. Applied Economics Letters, 24(15), 1097-1101.

Kurita, T. (2010). A Forecasting Model for Japan"s Unemployment Rate. Eurasian Journal of Business and Economics, 3(5), 127-134.

Milas, C., & Rothman, P. (2008). Out-of-sample forecasting of unemployment rates with pooled STVECM forecasts. International Journal of Forecasting, 24(1), 101-121.

Mohammadi, H., & Su, L. (2010). International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models. Energy Economics, 32(5), 1001-1008.

Montgomery, A. L., Zarnowitz, V., Tsay, R. S., & Tiao, G. C. (1998). Forecasting the US unemployment rate. Journal of the American Statistical Association, 93(442), 478-493.

Moshiri, S., & Brown, L. (2004). Unemployment variation over the business cycles: a comparison of forecasting models. Journal of Forecasting, 23(7), 497-511.

Nkwatoh, L. (2012). Forecasting unemployment rates in Nigeria using univariate time series models. International Journal of Business and Commerce, 1(12), 33-46.

Nyoni, T. (2018). Modeling and Forecasting Inflation in Kenya: Recent Insights from ARIMA and GARCH analysis. Dimorian Review, 5(6), 16-40.

Nyoni, T., & Nathaniel, S. P. (2018). Modeling rates of inflation in Nigeria: an application of ARMA, ARIMA and GARCH models.

Ong, C. S., Huang, J. J., & Tzeng, G. H. (2005). Model identification of ARIMA family using genetic algorithms. Applied Mathematics and Computation, 164(3), 885-912.

Proietti, T. (2003). Forecasting the US unemployment rate. Computational Statistics & Data Analysis, 42(3), 451-476.

Sigauke, C., & Chikobvu, D. (2011). Prediction of daily peak electricity demand in South Africa using volatility forecasting models. Energy Economics, 33(5), 882-888.

Simionescu, M. (2013). The Performance of Unemployment Rate Predictions in Romania. Strategies to Improve the Forecasts Accuracy. Review of Economic Perspectives, 13(4), 161-175.

Tan, Z., Zhang, J., Wang, J., & Xu, J. (2010). Day-ahead electricity price forecasting using wavelet transform combined with ARIMA and GARCH models. Applied Energy, 87(11), 3606-3610.

Tran, Q. T., Ma, Z., Li, H., Hao, L., & Trinh, Q. K. (2015). A multiplicative seasonal ARIMA/GARCH model in EVN traffic prediction. International Journal of Communications, Network and System Sciences, 8(04), 43.

Xu, W., Li, Z., Cheng, C., & Zheng, T. (2013). Data mining for unemployment rate prediction using search engine query data. Service Oriented Computing and Applications, 7(1), 33-42.

Yaziz, S. R., Azizan, N. A., Zakaria, R., & Ahmad, M. H. (2013, December). The performance of hybrid ARIMA-GARCH modeling in forecasting gold price. In 20th International Congress on Modelling and Simulation, Adelaide (pp. 1-6).

Zhang, Y., Haghani, A., & Zeng, X. (2014). Component GARCH models to account for seasonal patterns and uncertainties in travel-time prediction. IEEE Transactions on Intelligent Transportation Systems, 16(2), 719-729.
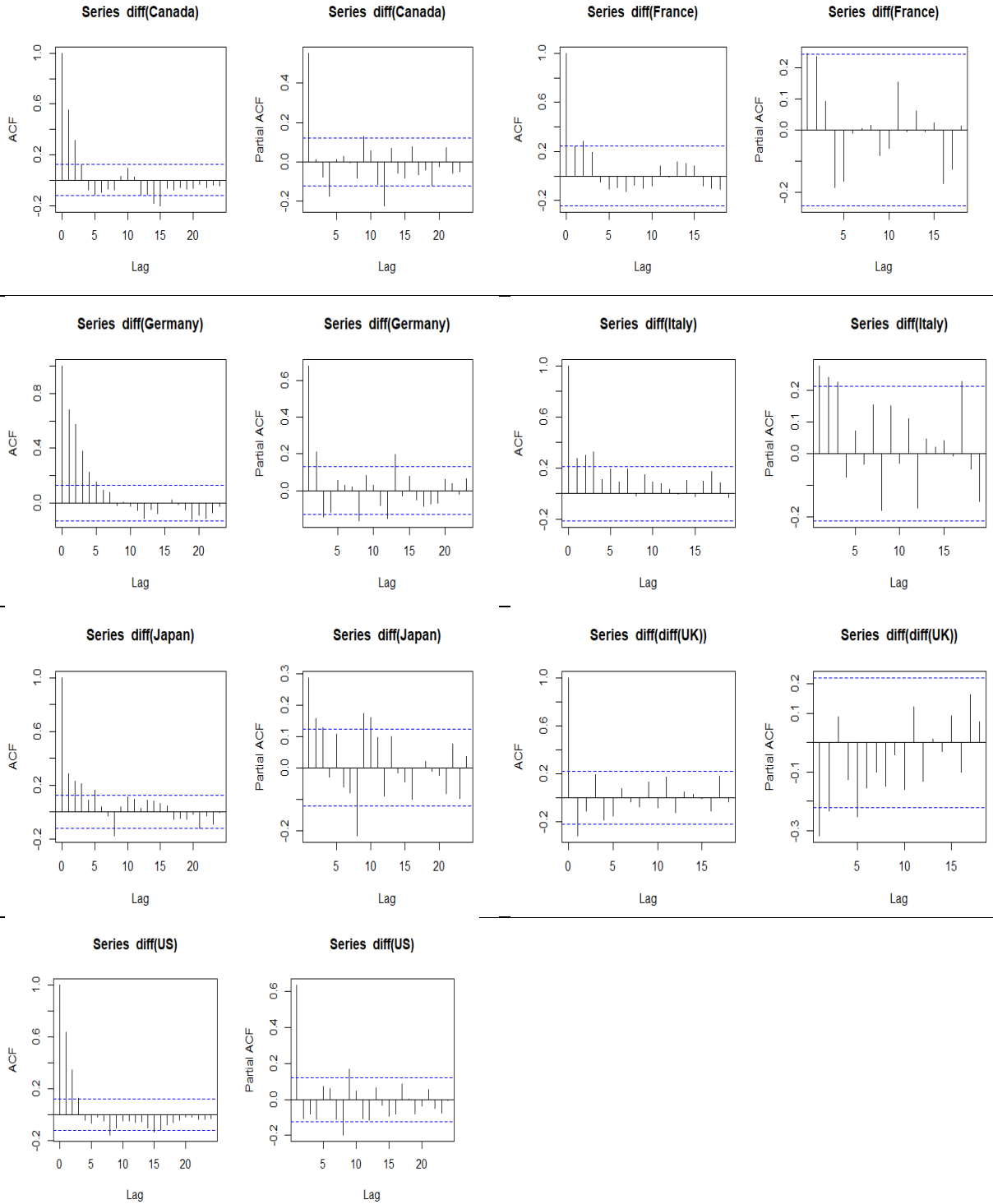
Appendix

Figure A-1: Auto correlation (ACF) and partial auto correlation diagrams of differenced series of G7 countries' quarterly unemployment data.

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)