UNIVARIATE MODELLING STRATEGIES FOR EUROZONE HARMONIZED UNEMPLOYMENT RATE

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Abstract

One of the prominent features of most economic data is that these type of data can usually be exposed to non-stationarity with significant seasonal patterns at frequencies measured with the exception of annual basis, and time series forecasting approaches require identifying the knowledge of seasonal components if available. Unemployment expectations and movements are crucial components in characterizing intense business cycle fluctuations and play a large role in their predictive modelling. In this paper, it has been aimed to analyze the seasonal characteristics of Eurozone harmonized unemployment rate at quarterly frequency using univariate modelling techniques, or more specifically to investigate which type of seasonality -deterministic or stochastic- accounts for the series in the best way based on the knowledge of whether the series follows a seasonally integrated process or not. It has been utilized from seasonally unadjusted data in order to take seasonal patterns into account and the covered time span for the research is 1993Q1-2021Q1. Apart from Dickey, Hasza & Fuller (DHF) (1984) and Hylleberg, Engle, Granger & Yoo (HEGY) (1990) test procedures for seasonal integration and seasonal dummy model; Lagrange-Multiplier based Canova & Hansen (CH) (1995) test as grounded upon the methodology of Nyblom (1989) and Hansen (1990) with the null hypothesis of deterministic seasonality has also been implemented. Findings of the research have indicated that according to DHF test, the series in question does not manifest a seasonally integrated of order one process; HEGY procedure covering two auxiliary regression models (with "Constant & Seasonal Dummies"; "Constant, Trend & Seasonal Dummies") reveals the absence of a seasonal unit root only for 4 quarters per cycle (i.e. annual cycle) for 5% significance level; CH test regression results imply the stability of seasonal intercepts for all seasons at 5% significance level, but Eurozone harmonized unemployment rate seems to subject to structural change only in the second quarter for 10% critical value and all seasonal cycles related to $\pi / 2$ & π frequencies are jointly stationary at 5% significance level, but not at 10%. In brief, all regression models along with CH test regression have confirmed consistently that harmonized unemployment rate series for the Eurozone exhibits stationary seasonality for 5% significance level. Furthermore, deterministic seasonal effects have been computed through the trigonometric representation.

***Keywords**: Deterministic Seasonality, Harmonized Unemployment Rate, Seasonal Integration, Canova-Hansen (CH) Test, HEGY Test*

1. INTRODUCTION

Handling pure analysis of seasonality and specifying it precisely in the deterministic time series indicators of the economic system for being able to choose a proper policy analysis and implementing it for the relevant economy are of great importance. Depending on this, the removal of the information on seasonal factors regarding an economic variable as in seasonal adjustment transaction renders the policy maker to differentiate between the seasonal and long run variations in a variable and thereby design appropriate policy responses possible (Hansda, 2012: 1673). Whether there is a possible expansion or recession in the economy; when being confronted with a remarkable drop -for instance, in industrial production- in the first quarter of the year, it is quite consequential for analysts to make inference about whether a first quarter dip is caused by seasonal factors that will vanish next quarter or whether the decline is an indicator for a change in the business cycle from boom to bust (Jaditz, 1994: 17). Starting from here, we can understand how important it is for the economy not to disregard the nature of seasonality. Although the seasonal adjustment procedure facilitates to keep the track of trend and cyclical fluctuations; for being able to observe seasonal movements, this paper takes the seasonally-unadjusted series as basis. One supportive justification favor to using the seasonally unadjusted variables lies in unit root tests; such that unit root tests reveal more powerful properties in the case of seasonally-unadjusted series due to the fact that the usage of seasonally-adjusted data will conclude in a bias in Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) statistics toward non-rejection of the unit root (Maddala & Kim, 1998: 364-365).

Fluctuations in unemployment and unemployment expectations are crucial in characterizing business cycle fluctuations and their predictive modelling. There are plentiful literature studies dealing with the seasonality in unemployment rates and focusing on predicting them -especially utilizing from Seasonal Autoregressive Integrated Moving Average (SARIMA) models-. Pierce (1978) investigates the seasonality in U.S. unemployment rate for the period covering 1947-1975 and determines the presence of stochastic seasonality in the series via examining remaining seasonality after the regression. In the study by Franses (1998), whether seasonality in unemployment rates displays an alteration depending on the business cycles or not is investigated through a seasonal smooth transition autoregression (STAR) model and as a result, changing pattern of seasonality is pointed out for the data at quarterly frequency regarding 10 countries (Löf, 2001). Jaditz (2000) analyzes nine time series including unemployment rate which was obtained from Bureau of Labor Statistics for the period January 1970 - December 1998. The findings show that the unemployment rate features significant deterministic and stochastic seasonality patterns in both mean and variance. Crespo (2001) generalizes "Self-Exciting Threshold Autoregressive" (SETAR) model -taking deterministic seasonality into acccount- to the seasonal SETAR framework for quarterly U.S. and Japan unemployment rates. Desaling (2016) aims to forecast and model the behavior of Sweden unemployment rate in the context of both univariate and multivariate time series covering the period 1983Q1-2015Q4 where the last 20 observations are used to assess the performance of the model forecasting. In the study, SETAR model and SARIMA model as a stochastic seasonal model have been used as univariate modelling techniques. HEGY test results show that unemployment rate does not include seasonal unit roots at semi-annual and annual frequencies, but includes a non-seasonal unit root. As a result, SARIMA $(4,1,3)(0,0,1)_4$ model has been chosen as the suitable univariate model for Swedish unemployment rate. In their study, Dritsakis & Klazoglou (2018) try to determine the most suitable model of U.S. unemployment rates for forecasting -covering the period 1955M1–2017M7- and they find the SARIMA$(1,1,2)(1,1,1)_{12}$–GARCH(1,1) model [GARCH: Generalized Autoregressive Conditional Heteroskedasticity] as the best performing forecasting model. Abdikader (2019) presents an analysis to forecast the Canadian unemployment rate for the period January 1976-December 2018 by utilizing from SARIMA, seasonal random walk and autoregressive distributed lag (ARDL) models where the modification of ARDL model is in a way to include West Texas Intermediate (WTI) spot price of oil as a leading indicator variable. As a conclusion, HEGY test findings reveal the existence of unit roots at 4 months per cycle & 3 months per cycle frequencies for models with both "intercept" and "intercept & trend", and the most accurate models for forecasting have been found to be ARIMA$(||1,3,5||,0,0)(0,1,1)_{12}$ and ARIMA$(||3,4,5||,1,0)(0,1,1)_{12}$. Most recently; Davidescu et al. (2021) aim to specify the most suitable model for Romanian unemployment rate, detect whether there is a seasonal pattern in the given series or not and forecast the unemployment rate using univariate forecasting modelling techniques (SARIMA, SETAR, Holt–Winters, ETS (error, trend, seasonal), neural network autoregression (NNAR)) for the sample period January 2000-December 2020. According to the findings, they reveal that Romanian unemployment rate displays clear strong seasonal patterns over the training set (2000M1–2017M12) and features non-stationarity as integrated of order one by non-representing stochastic seasonality; and also it is characterized with NNAR according to the root mean squared error (RMSE) & mean absolute error (MAE) forecast performance measures and with SARIMA based on the mean absolute percent error (MAPE) measure as the best performing models.

In this study, it has been aimed to determine a suitable model in the univariate context for quarterly Eurozone harmonized unemployment rate that covers the period 1993Q1-2021Q1 by carrying out Dickey, Hasza & Fuller (DHF) (1984); Hylleberg, Engle, Granger & Yoo (HEGY) (1990) and Canova & Hansen (CH) (1995) test procedures which will shed light on discovering if the series is seasonally integrated or not and identifying the type of seasonality - deterministic or stochastic- in Eurozone harmonized unemployment rate. The remainder of this paper has been structured as follows: Section 2 presents the methodological framework for univariate seasonality modelling, Section 3 discusses empirical findings, and the conclusion part outlines general inferences of the study.

2. METHODOLOGICAL FRAMEWORK

2.1. Deterministic Seasonality and Its Representations

Deterministic seasonality gives a description of varying unconditional mean behavior with the season of the year, identifies the known part of the seasonal cycle when "the process is started" and is limited to time constant seasonal means showing differences across quarters/months (Kunst, 2012). For simplicity, assuming that $t=1$ corresponds to the first season of the year and s denotes the season in which observation t falls; a y_t series could be written as identical to $y_{s\tau}$, where $s=1+[(t-1)\bmod S]$ (that is, s_t is one plus the integer remainder obtained when $t-1$ is divided by S which denotes the number of observations per year) and $\tau=1+\text{int}[(t-1)/S]$ which is a notation for the year in which a specific observation t falls with "int" denoting the integer part. If there are T observations in y_t series, we will suppose that there are exactly T_τ years of data; so that $T_\tau = T/S$.

There exist two types of representations reflecting deterministic seasonality as the dummy variable representation and the trigonometric representation. The most frequently used dummy variable representation of deterministic seasonality in the general sense can be identified as in Equation (1):

$$y_t = \sum_{s=1}^{S} \gamma_s \delta_{st} + z_t \ , \quad t = 1, \ldots\ldots\ldots, T_\tau \tag{1}$$

where y_t is a univariate process, δ_{st} is a seasonal dummy variable taking the value 1 in season s (that is, $\delta_{st}=1$ if $s_t = s$ for $s=1,\ldots..,$S) and 0 otherwise; and finally the process z_t is a weakly stationary stochastic process with mean zero. Thus; for season s of year, the representation $E(y_{s\tau}) = \gamma_s$ will be valid for $s=1,\ldots..,$S implying that the process has a seasonally shifting mean. However, this representation exhibits a disadvantage with respect to not being able to distinguish seasonality from the overall mean when the latter is nonzero. The overall mean of y_t series is specified as $E(y_t) = \mu = (1/S)\sum_{s=1}^{S}\gamma_s$ and the deterministic seasonal effect m_s is computed as $m_s = \gamma_s - \mu$ which implies that in case observations are summed over a year, there will be no deterministic seasonality. Additionally, the sum of all deterministic seasonal effects will be equal to zero.

Apart from the dummy variable representation, the trigonometric representation of deterministic seasonality can be shown as

$$y_t = \mu + \sum_{k=1}^{S/2}\left[\alpha_k \cos\left(\frac{2\pi k t}{S}\right) + \beta_k \sin\left(\frac{2\pi k t}{S}\right)\right] + z_t \tag{2}$$

where

$$\alpha_k = \frac{2}{S}\sum_{s=1}^{S} m_s \cos\left(\frac{2\pi k j}{s}\right), \quad k = 1, 2, \ldots\ldots, \frac{S}{2} \tag{3}$$

$$\alpha_{S/2} = \frac{1}{S}\sum_{s=1}^{S} m_s \cos(\pi j) \tag{4}$$

$$\beta_k = \frac{2}{S}\sum_{s=1}^{S} m_s \sin\left(\frac{2\pi kj}{s}\right) \ , \ k = 1,2,\ldots\ldots,\frac{S}{2}-1 \qquad (5)$$

In Equation (2), the second component in the right hand side of the representation considers β_k only for $k = 1,2,\ldots..,\frac{S}{2}-1$. This is due to the fact that $\beta_{S/2}$ multiplies a sine term which is always equal to zero. For the case of quarterly data (S=4), the seasonal dummy variable coefficients of Equation (1) and the deterministic factors in the trigonometric representation are associated with one another as in the following:

$$\begin{aligned}\gamma_1 &= \mu + \beta_1 - \alpha_2 \\ \gamma_2 &= \mu - \alpha_1 + \alpha_2 \\ \gamma_3 &= \mu - \beta_1 - \alpha_2 \\ \gamma_4 &= \mu + \alpha_1 + \alpha_2\end{aligned} \qquad (6)$$

with α_1 and β_1 representing the annual wave and α_2 representing the half-year component (Kunst, 2012). (6) can also be stated differently as:

$$\Gamma = R.B\,, \qquad (7)$$

where $\Gamma = (\gamma_1,\gamma_2,\gamma_3,\gamma_4)'$, $B = (\mu,\alpha_1,\beta_1,\alpha_2)'$ and

$$R = \begin{bmatrix} 1 & 0 & 1 & -1 \\ 1 & -1 & 0 & 1 \\ 1 & 0 & -1 & -1 \\ 1 & 1 & 0 & 1 \end{bmatrix} \qquad (8)$$

This 4x4 non-singular matrix handles the one-to-one relationship between the dummy variable and the trigonometric representations for the quarterly case. Equation (7) can also be applied to data measured at different frequencies other than quarterly. For instance, in the case of monthly data (S=12), the seasonal frequencies will emerge as $\frac{\pi}{6},\frac{\pi}{3},\frac{\pi}{2},\frac{2\pi}{3},\frac{5\pi}{6}$ and π. Let us consider again the general case of S seasons. There are some good properties for the matrix R in Equation (8): When μ is incorporated into the vector B, the matrix R becomes a square matrix and must be non-singular because there is a one-to-one relationship between two representations of deterministic seasonality. Besides, orthogonality characteristic of the columns of the matrix R to one another implies that when the vector R_i represents the *i*th column, so that $R = (R_1,\ldots\ldots, R_S)$; then $R_i{}' R_j = 0,\ i \neq j$ and thus it is guaranteed that $R'R = D$ is a diagonal matrix. So, if the *i*th diagonal element of D is shown as d_i, then

$$R^{-1} = \begin{bmatrix} \frac{1}{d_1} R_1{}' \\ \frac{1}{d_2} R_2{}' \\ \vdots \\ \frac{1}{d_s} R_S{}' \end{bmatrix} \qquad (9)$$

so that the inverse of R becomes the transpose of itself (Ghysels & Osborn, 2001).

2.2. DHF Test

Dickey et al. (1984) have proposed DHF test for seasonal integration that is also modified by Osborn et al. (1988) and emerges as the generalization of the ADF test. The null hypothesis of the test is $y_t \sim SI(1)$ which says that the series in interest follows a seasonally integrated of order 1 process. Using DHF test for seasonal integration is equivalent to testing for stochastic seasonality. Supposing that the data generating process is known to be a seasonal autoregressive process of order one (SAR(1)) $[y_t = \phi_s y_{t-s} + \varepsilon_t]$, then the DHF test can be parameterized as

$$\Delta_s y_t = \alpha_s y_{t-s} + \varepsilon_t \qquad (10)$$

where $\alpha_s = -(1-\phi_s)$. In Equation (10), the null hypothesis of seasonal integration is $\alpha_s = 0$ and the alternative of a stationary stochastic seasonal process implies $\alpha_s < 0$ (Baltagi, 2001: 661). For more information about DHF test regressions in order to determine the seasonal integration order of a variable, see Charemza and Deadman (1992).

2.3. HEGY TEST

Ghysels et al. (1994) point out to that DHF testing procedure seems unable to separate unit root at zero frequency or at one of seasonal frequencies of data generating processes with nonstationarity induced by the $(1-L^4)$ factor and therefore HEGY procedure which is proposed by Hylleberg et al. (1990) is more advantageous than DHF test. Box & Jenkins (1970) have proposed a very-well recognized seasonal differencing operator. Subsequent to them, Grether & Nerlove (1970) and Bell & Hillmer (1984) have utilized from this operator as a seasonal process. In the case of quarterly data, the factorization of seasonal differencing operator takes the form of

$$\begin{aligned}\Delta_4 y_t &= (1-L^4) y_t = (1-L)(1+L+L^2+L^3) y_t \\ &= (1-L)(1+L)(1+L^2) y_t = (1-L)(1+L)(1-iL)(1+iL) y_t \\ &= (1-L) S(L) y_t\end{aligned} \qquad (11)$$

where $S(L) = (1+L)(1+L^2)$ and i represents an imaginary part of a complex number such that $i^2 = -1$. Based on this factorization, the presence of four roots with modulus of one can be mentioned for quarterly stochastic seasonal unit root process: one is $(1-L)$ denoting zero frequency that removes the trend component. Amongst the other (seasonal) roots represented by $(1+L)$, $(1-iL)$ and $(1+iL)$; the first root is at 2 cycles per year (π frequency, semi-annual) and the other two roots are complex pairs at 1 cycle per year ($\pi/2$ ($3\pi/2$) frequencies, annual) (Charemza & Deadman, 1997: 108).

HEGY testing procedure for seasonal unit roots can be expressed as follows:

$$\Delta_4 y_t = \sum_{i=1}^{4} \alpha_i D_{i,t} + \sum_{i=1}^{4} \pi_i Y_{i,t-1} + \sum_{i=1}^{k} c_i \Delta_4 y_{t-i} + \varepsilon_t \qquad (12)$$

where k represents the number of lagged terms which should be contained in test regression to ensure that residuals are white noise, the $D_{i,t}$ are seasonal dummy variables and the $Y_{i,t}$ variables are constructed from the series on y_t as:

$$Y_{1,t} = (1+L)(1+L^2) y_t = y_t + y_{t-1} + y_{t-2} + y_{t-3} \qquad (13)$$

$$Y_{2,t} = -(1-L)(1+L^2)y_t \;\; = -y_t + y_{t-1} - y_{t-2} + y_{t-3} \quad (14)$$

$$Y_{3,t} = -(1-L)(1+L)y_t \;\; = -y_t + y_{t-2} \quad (15)$$

$$Y_{4,t} = -(L)(1-L)(1+L)y_t \;\; = Y_{3,t-1} = -y_{t-1} + y_{t-3} \quad (16)$$

(Charemza & Deadman, 1992).

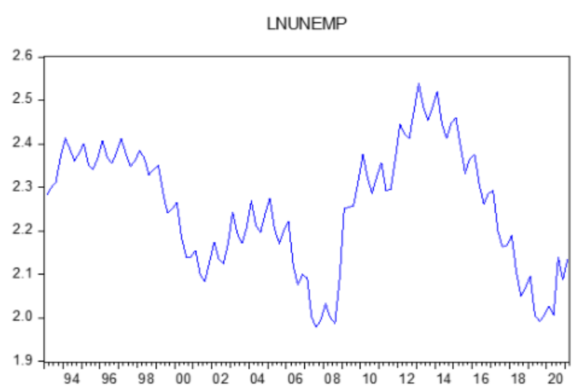
The null hypothesis of the HEGY test is that the variable in interest is seasonally integrated. Therefore, if the null hypothesis of stochastic seasonality is true, all the $\alpha_i s$ will be equal to one another and all the $\pi_i s$ will be identical to zero. For Equation (12), $H_0 : \pi_1 = 0$ (the existence of nonseasonal unit root) and $H_0 : \pi_2 = 0$ (the existence of biannual unit root) null hypotheses are tested using *t* tests against the hypotheses that $\pi_i < 0$. $H_0 : \pi_3 = \pi_4 = 0$ (the existence of annual unit root) null hypothesis is tested through F test against the alternative hypothesis H1: $\pi_3 \neq \pi_4 \neq 0$ (Hylleberg et al., 1990: 221-223). This test regression can be expanded with both intercept and trend deterministic components. In case the intercept is incorporated into the test regression, three seasonal dummy variables should be used not to fall into the dummy variable trap.

For the sake of saving space, Canova & Hansen (CH) (1995) test will not be discussed in details here. But if necessary to express in concise, Canova & Hansen (1995) propose CH test –based on the methodology of Nyblom (1989) and Hansen (1990) who designed Lagrange Multiplier (LM) tests for parameter instability– with the null hypothesis of no unit roots at seasonal frequencies against the alternative of a unit root at either a specific seasonal frequency or a set of selected seasonal frequencies; and depending on this, the null hypothesis of CH test can be said to imply the existence of stationary seasonality (i.e. deterministic seasonality exists) rather than non-stationary seasonality.

3. DATA AND EMPIRICAL FINDINGS

The quarterly harmonized unemployment rate (in percent) data used in the study for the Eurozone have been obtained from Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis as not seasonally-adjusted. The covered time span for the research is 1993Q1-2021Q1. The logarithmic transformation (LNUNEMP) has been applied for the harmonized unemployment rate and the transformed variable has been graphed in Figure 1:

Figure 1. Graph of Logarithmic Harmonized Unemployment Rate Series



As discussed in Section 2, there are two representations of deterministic seasonality as dummy variable and trigonometric representations. Starting from here, at first the presence of deterministic seasonality has been investigated using seasonal dummy model as the most fundamental deterministic model of seasonality. Seasonal dummy variable regression results have been reported in Table 1.

Table 1. Dummy Variable Representation of Eurozone Harmonized Unemployment Rate

Dependent Variable: DLNUNEMP				
Variable	Coefficient	Std. Error	*t*-statistic	Prob.
D1	0.045636	0.009014	5.063099	0.0000
D2	-0.058550	0.009042	-6.475311	0.0000
D3	-0.019833	0.009611	-2.063647	0.0416
D4	0.027363	0.011479	2.383840	0.0190
DLNUNEMP(-1)	0.229559	0.097042	2.365557	0.0199
DLNUNEMP(-2)	0.055082	0.118343	0.465443	0.6426
DLNUNEMP(-3)	0.267805	0.131220	2.040895	0.0438
R-squared: 0.677552 Adjusted R-squared: 0.658584 Durbin-Watson (DW) Stat.: 2.034592				

Seasonal dummy regression has been carried out for the first-differenced logarithmic Eurozone harmonized unemployment series (DLNUNEMP). As a conclusion, all seasonal dummy variables have been found to be significant at 5% significance level.

Next, let us deal with the trigonometric representation. First of all, Γ matrix which is structured on the seasonal means in the dummy variable representation can be specified as

$$\Gamma = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \end{pmatrix} = \begin{pmatrix} 0.045636 \\ -0.058550 \\ -0.019833 \\ 0.027363 \end{pmatrix}$$

In this case, the matrix of the parameters B as related to the trigonometric representation can be computed as follows:

$$B = \begin{pmatrix} \mu \\ \alpha_1 \\ \beta_1 \\ \alpha_2 \end{pmatrix} = R^{-1}\Gamma = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0 & -0.5 & 0 & 0.5 \\ 0.5 & 0 & -0.5 & 0 \\ -0.25 & 0.25 & -0.25 & 0.25 \end{bmatrix} \begin{pmatrix} 0.045636 \\ -0.058550 \\ -0.019833 \\ 0.027363 \end{pmatrix} = \begin{pmatrix} -0.001346 \\ 0.0429565 \\ 0.0327345 \\ -0.0142475 \end{pmatrix}$$

Depending on Equations in (6), the components of B matrix can be verified as follows:

$$\gamma_1 = \mu + \beta_1 - \alpha_2 = -0.001346 + 0.0327345 - (-0.0142475) = 0.045636$$

$$\gamma_2 = \mu - \alpha_1 + \alpha_2 = -0.001346 - (0.0429565) + (-0.0142475) = -0.05855$$

$$\gamma_3 = \mu - \beta_1 - \alpha_2 = -0.001346 - (0.0327345) - (-0.0142475) = -0.019833$$

$$\gamma_4 = \mu + \alpha_1 + \alpha_2 = -0.001346 + 0.0429565 + (-0.0142475) = 0.027363$$

where the overall mean μ is computed as $E(y_t) = \frac{1}{4}(\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4)$:

$$\mu = E(y_t) = \frac{1}{4}(0.045636 - 0.05855 - 0.019833 + 0.027363) = -0.001346$$

On the other hand, deterministic seasonal effect (m_s) that is specific to a season s can be obtained through $m_s = \gamma_s - \mu$ and the sum of all deterministic seasonal effects must be equal to zero:

$$m_1 = 0.045636 - (-0.001346) = 0.046982$$
$$m_2 = -0.05855 - (-0.001346) = -0.057204$$
$$m_3 = -0.019833 - (-0.001346) = -0.018487$$
$$m_4 = 0.027363 - (-0.001346) = 0.028709$$
$$m_1 + m_2 + m_3 + m_4 = 0.046982 - 0.057204 - 0.018487 + 0.028709 = 0$$

Besides, these deterministic seasonal effects can be used for computing the parameters α_1, α_2 and β_1 which take place in the matrix *B*:

$$\alpha_1 = \frac{1}{2}\sum_{s=1}^{4} m_s \cos\left(\frac{s\pi}{2}\right) = \frac{1}{2}(-m_2 + m_4) = \frac{1}{2}(0.057204 + 0.028709) = 0.0429565$$
$$\alpha_2 = \frac{1}{4}\sum_{s=1}^{4} m_s \cos(s\pi) = \frac{1}{4}(-m_1 + m_2 - m_3 + m_4) = \frac{1}{4}(-0.046982 - 0.057204 + 0.018487 + 0.028709) = -0.0142475$$
$$\beta_1 = \frac{1}{2}\sum_{s=1}^{4} m_s \sin\left(\frac{s\pi}{2}\right) = \frac{1}{2}(m_1 - m_3) = \frac{1}{2}(0.046982 + 0.018487) = 0.0327345$$

Table 2. DHF Test Results for Quarterly Eurozone Harmonized Unemployment Series

Dependent Variable: D4Y				
Variable	Coefficient	Std. Error	*t*-statistic	Prob.
D1	0.164903	0.050191	3.285502	0.0014
D2	0.159882	0.049330	3.241110	0.0016
D3	0.163209	0.048770	3.346469	0.0012
D4	0.155583	0.049734	3.128326	0.0023
LNUNEMP(-4)	-0.071605	0.021795	**-3.285372**	0.0014
D4Y(-1)	1.219719	0.093602	13.03094	0.0000
D4Y(-2)	-0.332932	0.092526	-3.598270	0.0005
R-squared: 0.893196		Adjusted R-squared: 0.886788	DW stat: 2.025928	

Table 2 presents DHF test results for Eurozone harmonized unemployment series. The dependent variable D4Y has been identified as ($LNUNEMP_t - LNUNEMP_{t-4}$). LNUNEMP(-4) variable represents y_{t-4} in Equation (10). Apart from seasonal dummy variables, first and second lagged terms of the dependent variable have been included into the DHF test regression as shown in Table 2 (lags have been determined in a way to make sure about white noise residuals). Here, critical t-value of the DHF test statistic has been taken as equal to the ADF test statistic. Thus, ADF critical value which is -1.95 for 5% significance level has been used. In conclusion, based on the calculated t-statistic for LNUNEMP(-4) variable (-3.285372), it can be inferred that the null hypothesis saying that the variable in interest follows a seasonal integration of order 1 process can be rejected and thus, Eurozone harmonized unemployment rate exhibits a stationary stochastic seasonal process according to DHF test results.

Table 3 presents HEGY test findings for “Constant & Seasonal Dummies” model. According to the Akaike and Schwarz information criteria, the optimal lag length regarding the addition of lagged values of the dependent variable into the regression has been chosen as 2 in order to ensure white-noise residuals. In Table 3, coefficients for Y11, Y21, Y31, Y41 represent π_1, π_2, π_3 and π_4 respectively. Here, the null hypothesis for HEGY test means that π_1, π_2, π_3 and π_4 are simultaneously equal to zero (existence of all unit roots). Critical HEGY test values have been obtained from Hylleberg et al. (1990) for 5% significance level. When calculated *t*-statistics (-2.234067, -1.344188, -0.665095, -3.759765) are evaluated, it is seen that $\pi_1 = 0$, $\pi_2 = 0$, $\pi_3 = 0$ hypotheses (except $\pi_4 = 0$) cannot be rejected. The presence of unit roots has been detected for 0, π and $\pi/2$ frequencies; however, there is no unit root at $3\pi/2$ frequency in the unemployment rate series.

Table 3. HEGY Test Results for "Constant & Seasonal Dummies" Model

Dependent Variable: D4Y			
Variable	**Coefficient**	**Std. Error**	***t*-statistic**
C	0.113696	0.049635	2.290625
D1	0.036310	0.019317	1.879624
D2	-0.022615	0.023678	-0.955112
D3	-0.031047	0.015221	-2.039769
Y11	-0.012225	0.005472	-2.234067
Y21	-0.263733	0.196203	-1.344188
Y31	-0.099727	0.149944	-0.665095
Y41	-0.490747	0.130526	-3.759765
D4Y(-1)	0.833453	0.247647	3.365493
D4Y(-2)	-0.365630	0.139116	-2.628244
R-squared: 0.906511	Adjusted R-squared: 0.897837	DW stat: 1.965573	
Null Hypothesis	**Simulated P-Value**	**Statistical**	
Zero Frequency	0.214438	-2.234067	
2 quarters per cycle	0.627958	-1.344188	
4 quarters per cycle	0.008358	7.883009	

Besides, Table 3 reports simulated probability values for $\pi_1 = 0$, $\pi_2 = 0$, $\pi_3 = \pi_4 = 0$ null hypotheses respectively. According to the results for 1000 Monte Carlo simulations, we can mention about the existence of only nonseasonal and semi-annual unit roots, since the simultaneous existence of annual unit roots has been rejected with 0.008358 prob-value. Therefore, since there is no evidence about the simultaneous existence of all four unit roots according to the HEGY test results, it can be said that Eurozone harmonized unemployment rate cannot be described by a seasonally integrated of order 1 process. As a conclusion, HEGY test findings have supported the DHF test findings.

Table 4. HEGY Test Results for "Constant, Trend & Seasonal Dummies" Model

Dependent Variable: D4Y		
Null Hypothesis	**Simulated P-Value**	**Statistical**
Zero Frequency	0.491986	-2.240008
2 quarters per cycle	0.653493	-1.318072
4 quarters per cycle	0.015374	7.844997

Table 4 reveals HEGY test results for "Constant, Trend & Seasonal Dummies" model. According to this, the findings support those found in Table 3 so that there exist only nonseasonal (zero frequency) and semi-annual unit roots in the series for 5% significance level. Since the simultaneous existence of annual unit roots has been rejected with 0.015374 prob-value, it is concluded that Eurozone harmonized unemployment rate does not exhibit a seasonally integrated of order 1 process.

Table 5. CH Test Results

Frequencies	LM Statistical	1%	5%	10%
4 quarters per cycle	0.479134	1.070	0.749	0.610
2 quarters per cycle	0.422193	0.748	0.470	0.353
Joint test	1.003962	1.350	1.010	0.846

Seasonal Intercept	LM Statistical	1%	5%	10%
1	0.090262	0.748	0.470	0.353
2	0.408510	0.748	0.470	**0.353**
3	0.235792	0.748	0.470	0.353
4	0.256463	0.748	0.470	0.353

Table 5 presents Canova-Hansen (CH) test results. As known, the null hypothesis of CH test states that the seasonal pattern is deterministic. CH joint test result (1.003962) implies that all seasonal cycles are jointly stationary for 1% and 5% significance levels, but this is not the case for 10% significance level which reports the nonstationarity of the cycles. On the other hand, CH test confirms the stability of seasonal intercepts for all seasons at 1%, 5% and 10% significance levels; excluding the case that Eurozone harmonized unemployment rate seems to subject to structural change in the second quarter for 10% level. As a conclusion, Eurozone harmonized unemployment rate displays deterministic seasonality for both 1% and 5% significance levels.

4. CONCLUSION

One of the most important features of economic and financial series is that they are exposed to seasonal effects. Accounting for seasonal patterns is of vital importance in time series analyses. In this study, it has been aimed to analyze the seasonal characteristics of Eurozone harmonized unemployment rate for the period covering 1993Q1-2021Q1, or more specifically to investigate which type of seasonality -deterministic or stochastic- is the best for the series based on the knowledge of whether the series follows a seasonal integrated process or not. To this end; it has been utilized from DHF, HEGY and CH test regressions as univariate modelling approaches regarding seasonality and seasonally-unadjusted series has been used for being able to take seasonal patterns into account. DHF and HEGY (based on 1000 Monte Carlo simulations) test results show that Eurozone harmonized unemployment rate does not display a seasonally integrated of order one process. Furthermore, the stability of seasonal cycles and intercepts has been investigated through CH test which is based on LM test statistics following the von-Mises distribution. According to CH test, seasonal cycles and seasonal intercepts for all seasons have been found to be stable at both 1% and 5% significance levels. Therefore, Eurozone harmonized unemployment rate variable manifests a deterministic seasonal pattern. In addition, there is no stability at seasonal intercept for only the second quarter at 10% significance level. In brief, all univariate modelling approaches regarding seasonality for Eurozone harmonized unemployment rate support one another in the sense of accepting stationary seasonality and this analysis is expected to shed light on designing effective policies for Eurozone harmonized unemployment rate and analyzing the seasonal behavior of the series.

UNIVARIATE MODELLING STRATEGIES FOR EUROZONE HARMONIZED UNEMPLOYMENT RATE

ORİJİNALLİK RAPORU

%16	%14	%8	%2
BENZERLİK ENDEKSİ	İNTERNET KAYNAKLARI	YAYINLAR	ÖĞRENCİ ÖDEVLERİ

BİRİNCİL KAYNAKLAR

1	dergipark.org.tr İnternet Kaynağı	%4
2	homepage.univie.ac.at İnternet Kaynağı	%2
3	mafiadoc.com İnternet Kaynağı	%1
4	iibfdergi.deu.edu.tr İnternet Kaynağı	%1
5	epdf.pub İnternet Kaynağı	%1
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