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CYCLICAL AND SEASONAL PATTERNS OF US UNEMPLOYMENT LEVEL DURING 1948-2020

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Abstract: The paper seeks to explore the cyclical and seasonal variations for the monthly level series of US unemployment during 1948m_1-2020m_1 using H. P. Filter model and the ARIMA(12, 0, 12) model. The decomposition of trends and cycles was done through TSL method. The forecast ARIMA(4, 1, 4) was tested as stable model in which volatility tends to equilibrium as also was found from Impulse Response Function. The seasonality was also verified through ARIMA(12, 0, 12) where GARCH(1, 1) was seen as declining nature of conditional variance having heteroscedasticity problem.

Key words: US unemployment, seasonal unemployment, cyclical unemployment, volatility, ARIMA model, ACF, PACF.

JEL codes: C20, E24, E32, E47, J64

I. INTRODUCTION

Generally, seasonality indicates fluctuations of a time series which recur with a frequency of less than a year. Seasonality depends on institutional, weather, festive and other factors which affect both demand and supply. Seasonal fluctuations are more forecastable than typical business cycle fluctuations. Various incentives for households and firms to borrow or save to smooth economic fluctuations throughout the course of the year can be created through predictability. The market generally changes by seasonality with regard to time, but market differences in space still persists. The distribution of fluctuations within a year can be unequal. Seasonal fluctuations may also be medium- and long-term changes over time, thus seasonality may constitute a non-stationary variable. Therefore, the analysis of seasonality cannot be brought to a simple determination of a value of seasonal fluctuations, while the specificity of the functioning of labour markets in a short period should consider various aspects of seasonality. Empirical studies show significant differences between individual national labour markets in the size and distribution of seasonal fluctuations. The impact on seasonal fluctuations is mainly caused by changes of a structural nature. Seasonal unemployment may occur as demands shift from one season to the next or people are unemployed at particular times of the year when demand for labour is lower than unusual. This category can include any workers whose jobs are dependent on a particular season. Official unemployment statistics will often be adjusted, or smoothed, to account for seasonal unemployment which is mostly unattractive and local workers leave to find more stable jobs elsewhere.

Cyclical variations occur due to the ups and downs recurring after a period from time to time during the course of four phases of a business cycle such as prosperity or boom, recession, depression, and recovery. Cyclical unemployment is the component of overall unemployment that results directly from cycles of economic upturn and downturn. Unemployment typically rises during recessions and declines during economic expansions. Cyclical unemployment generally rises during recessions and falls during economic expansions and is a major focus of economic policy. Cyclical unemployment is one factor among many that contribute to total unemployment, including seasonal, structural, frictional, and institutional factors. Cyclical unemployment equals current unemployment rate minus addition of frictional unemployment rate and structural unemployment rate. It is understood that high or low cyclical unemployment is only temporary and depends on length of the economic contraction caused by recession. When the economy enters and re-enters business cycles, the rate of unemployment continuously changes. Even, a market crash can cause recession which produces high cyclical unemployment.

The unemployment level of USA has been observed as seasonal as well as cyclical variations in the course of monthly data from 1948m_1 to 2020m_1. The characteristic of unemployment cycles are closely related with recessions which were faced by USA from 1948 to 2020. Since 1948, the end of the postwar period, the United States has experienced 11 recessions. In the following table 1, US recessions from 1948 to 2020 have been arranged showing the duration of recessions and the main causes from which it started and effect on GDP and the peak rate of unemployment chronologically. Over that span, the federal government has employed various methods to push back unemployment by adopting anti-cyclical fiscal and monetary policies and other reform measures.

In this paper author endeavours to study the nature of seasonal variations and cyclical fluctuations of US unemployment level from the monthly data from 1948m_1 to 2020m_1 using several econometric models and figures which have described the patterns of seasonality and cycles.

II. STUDY MATERIALS

Abbring et al. (2001) used CPS unemployment data of USA from 1968 Jan to 1992May for white male and female and non-white male and female and found seasonal fluctuations. The paper observed that aggregate unemployment incidence rates and durations are countercyclical and upward trending and contributes similar fluctuations in aggregate unemployment where aggregate durations to contemporaneous variation of aggregate exit probabilities and also found substantial

Table 1
US recessions

Year of recession	*period*	*Duration (months)*	*Decline in GDP(%)*	*Peak unemplo-yment rate(%)*	*Main causes of recession*
1949	1948Nov-1949Octo	11	-1.7	5.9	Inflation and unemployment
1953	1953July-1954May	10	-2.6	2.9	Inflation, Korean war
1958	1957may-1958apl	8	-3.7	6.2	Tight monetary policy
1960-61	1960Apl-1961Feb	10	-1.6	6.9	Rolling adjustment
1969-70	1969Dec-1970Nov	11	-0.6	5.5	Inflation, restrictive monetary policy
1973-75	1973Nov-1975March	16	-3.2	8.8	Oil crisis, vietnam war
1980	1980Jan-1980July	6	-2.2	7.8	Inflation, slow money supply
1981-82	1981July-1982Nov	16	-2.7	10.8	New Iran policy
1990	1990July-1991March	8	-1.4	6.8	Oil price hike, Iraq-Kuwait war, NAFTA
2000	2001Mar-2001Nov	8	-0.3	5.5	Collapse of dotcom bubble, 9/11 attack
2008	2007Dec-2009June	18	-5.1	10.0	Collapse of housing bubble, financial crisis
2020	2020March-				

Source: https://en. wikipedia. org/wiki/list_of_recession_in_the_united_states

seasonal fluctuations in US unemployment. The exit probabilities are low in the first and high in the third quarter. The individual exit probabilities out of unemployment decline over the duration of the unemployment spell. Sikder (1985) finds that variation in durations is the dominant force driving unemployment rate cyclically in the period from 1968 to 1982 which is verified by Baker (1992a) for the period from 1979 to 1988.

Shimer (2005) studied US unemployment using monthly data from 1951 to 2003 through H. P. Filter model (1997) and showed that unemployment is strongly countercyclical, vacancies is strongly procyclical and their correlation is -0.89 and elasticity is greater than one where vacancy unemployment ratio is stable in the face of large unemployment fluctuations with countercyclical vacancies. An increase in both unemployment and vacancies leads to generate a separation shock.

Geramew and Gourio (2018) studied employment in 13 industries in 47 states in USA during 1990-2016 and used employment data for 1956-2016 and industry level data from 1939 to 2016 to applyH. P. Filter model. Their findings suggested that US employment exhibits significant seasonality but seasonal variation declined in 1960s and mid 1980s and then remained stable but it differs across industries and across states showing heterogeneity in the amplitude of the seasonal cycle across states but there is no association between the two. Over all, during 1950-2010, 44 states experienced a decline in seasonal variation and only three experienced an increase. The median seasonality falls from 1. 48% to 1. 03%.

Ferraro (2013) used CPS micro monthly data of US unemployment from 1976 to 2013 and developed a search -and-matching model and generated realistic volatility of unemployment and job vacancies preserving downward sloping Beveridge curve. The paper produces counterfactual implications for the asymmetry properties of vacancies having positive skewness. The paper found a correlation of 0. 858 between unemployment and vacancies. It also estimated AR(1) for H. P. Filter seasonality adjusted output per worker during 1948-2011 and also calculated autocorrelations. The participation rate was asymmetric. For policy prescription the paper found state dependent impulse response functions.

Berger and Vavra (2012) verified that no conditional heteroskedasticity for shocks was found in the business cycle literature which were commonly described which suggested that asymmetric responses, instead of asymmetric shocks, are responsible for heteroskedasticity in the U. S. unemployment rate.

Diamond (2013) found multiple reasons in measuring efficiency parameter of the matching functions to vary during the business cycles which differ from recessions and recoveries. Author noticed a shift of Beveridge curve that can be measured a structural change. Thus the paper suggests a efficiency parameter of the standard aggregate matching function because Beveridge curve should not be viewed as a tight technical relationship between vacancies and unemployment.

Przekota and Rembeza (2018) studied seasonal fluctuations of employment in USA taking monthly data from US Bureau of Labor Statistics during 1976-2014 using TRAMO/SEATS procedure. The paper determined the potential difference among states which are subject to spatial regularity and relation with distribution of the fluctuations and their value and distinguished the seasonal component , harmonics , amplitudes, phase shifts and share of each harmonic in variance of the seasonal component. The paper also prescribed macroeconomic policy to stabilise employment in the cycles.

Ahn and Hamilton (2018) estimated US unemployment inflows and outflows during 1976 January -2017 June which were allowed for observed heterogeneity and direct effects of unemployment duration on unemployment probabilities. The paper measured the shocks of short, medium and long run variance of unemployment with specific historical episodes and concluded that the changes in the composition of new inflows into unemployment are the most important factor in economic recessions.

Chen *et al.* (2016) examined US employment and output taking data of temporary and permanent employment from Fed Reserve Bank of St. Louis during 1990-2015 and found out higher volatility of temporary employment than permanent employment and temporary employment is strongly procyclical and even there is a stronger correlation between temporary employment and output than permanent employment counterpart and positive shock was observed in the impulse response of temporary employment and the impulse response of permanent employment has increased moderately in USA during 1990-2015.

Bhowmik (2020) examined the nexus between growth and unemployment in USA during 1948-2016 where one significant upward structural break was found in 1971. The paper also found a significant cointegration between unemployment gap and output gap where residual autocorrelations confirmed seasonality due to asymmetric shocks with heteroscedasticity.

III. METHODOLOGY AND SOURCE OF DATA

The cubic trend line was fitted by semi-log model stated below.

$Log(x) = c + b_0t + b_1t^2 + b_2t^3$ where x = unemployment level of USA, c and b_i are constants and t is the time .

To find the volatility GARCH(1, 1) model has been used.

$$h_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \beta_1 h_{t-1}$$

Where $\epsilon_t = v_t \sqrt{h_t}$, v_t = white noise process, and the conditional variance of ϵ_t is given by

$E_{t-1}\, \epsilon^2_t = h_t$. Thus the conditional variance of ϵ_t is the ARMA process given by h_t.

Given T observations on a variable x_t, Hodrick-Prescott Filter model (1997) proposed interpreting the trend component g_t as a very smooth series that does not differ too much from the observed x_t. It is calculated as

$1/T\,\{\Sigma(x_t-g_t)^2 + \lambda/T\Sigma[(g_t-g_{t-1}) - (g_{t-1}-g_{t-2})]^2\}$ where Σ t = 1 to T, T=observations, λ = constant and minimise (g_t) from t = –1 to T.

When the smoothness penalty λ tends to zero, g_t would just be the series x_t itself, whereas when λ tends to infinity, the procedure amounts to a regression on a linear time trend (that is produces a series whose second difference is exactly zero). The common practice is to use a value λ = 14400 for monthly data series.

The solution is given by $g^* = (H'H + Q'Q)^{-1} H'x = A^*x$

The inferred trend g_t^* for any date t is thus a linear function of the full set of observations on x_t for all dates.

Where the vector $H(TxT) = [I_T(TxT)\ 0(Tx2)]$ and matrix Q(TxT)=

$$\begin{bmatrix} 1 & -2 & 1 & 0 & \cdots & \cdots & 0 & 0 & 0 \\ 0 & 1 & -2 & 1 & \cdots & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \cdots & -2 & 1 & 0 \\ 0 & 0 & 0 & 0 & \cdots & \cdots & 1 & -2 & 1 \end{bmatrix}$$

The paper assumes the ARIMA (4, 0, 4) and ARIMA (4, 1, 4) as forecast model following Beveridge and Nelson (1981) respectively which are stated below.

$$\text{Log}(x)_t = c+\alpha_1\log(x)_{t-1}+\alpha_2\log(x)_{t-2}+\alpha_3\log(x)_{t-3}+\alpha_4\log(x)_{t-4}+\epsilon_t + \beta_1\epsilon_{t-1} + \beta_2\epsilon_{t-2}+ \beta_3\epsilon_{t-3}+ \beta_4\epsilon_{t-4}$$

and

$$\text{dlog}(x)_t= c+\alpha_1\log(x)_{t-1}+\alpha_2\log(x)_{t-2}+\alpha_3\log(x)_{t-3}+\alpha_4\log(x)_{t-4} + \epsilon_t + \beta_1\epsilon_{t-1} +\beta_2\epsilon_{t-2}+\beta_3\epsilon_{t-3}+\beta_4\epsilon_{t-4}$$

where c = constant, α_i = coefficient of AR and β_i = coefficients of MA.

Similarly, ARIMA (12, 0, 12) can be written as

$$\text{Log}(x)_t = c + \alpha\log(x)_{t-12} + \epsilon_t + \beta\epsilon_{t-12}$$

Ljung and Box(1978) Q-statistic is calculated as

$$Q = T(T+2)\ \Sigma r^2_k/(T-k) \text{ where } k = 1 \text{ to } s$$

Autocorrelation Function (ACF) can be derived from the formula

$$\text{ACF} = \rho_s = a_1\rho_{s-1} + a_2\rho_{s-2} \text{ where } s = 1, 2, 3\ldots\ldots\ldots\ldots\ldots$$

And Partial Autocorrelation Function (PACF) can be derived from the formula

$$\Phi_{ss} = (\rho_s - \Sigma\phi_{s-1},{}_j\rho_{s-j})/(1-\Sigma\phi_{s-1},{}_j\rho_j) \text{ where } s = 3, 4, 5, \ldots\ldots\ldots\ldots, \phi_{sj}=\phi_{s-1}, j - \phi_{ss}\phi_{s-1}, {}_{s-j}, j = 1, 2, 3\ldots. s-1$$

Monthly unemployment data of USA from $1948m_1$ to $2020m_1$ have been collected from Federal Reserve Bank of St. Louis, Economic Research Division and retrieved from https://fred.stlouisfed.org.

IV. FINDINGS OF THE ECONOMETRIC MODELS

(i) Patterns of US unemployment

The simple cubic form of trend line of US unemployment from monthly data from $1948m_1$ to $2020m_1$ has been found as significant except at square of time variable. It is steady upward rising.

$$\underset{}{\text{Log}(x)=}\ \underset{(218.3)^*}{7.735} + \underset{(7.20)^*}{0.00254t} + \underset{(1.31)}{1.24E\text{-}06t^2} \underset{(-4.16)^*}{-2.98E\text{-}09t^3}$$

$R^2 = 0.732$, F = 785.07*, DW = 0.02, * = significant at 5% level.

In the Figure 1, the actual cycle of unemployment and trend unemployment with residuals are depicted where trend line is as like as concave pattern.

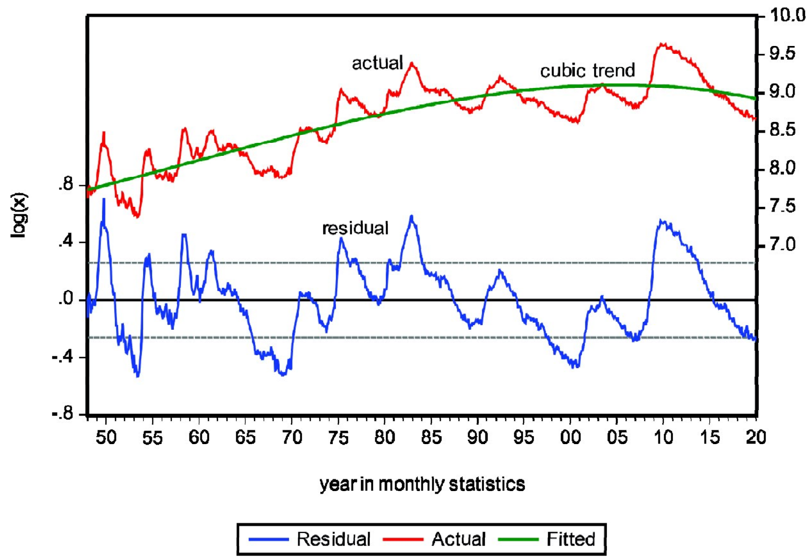


Figure 1: Estimated trend of us unemployment

Source: Plotted by author

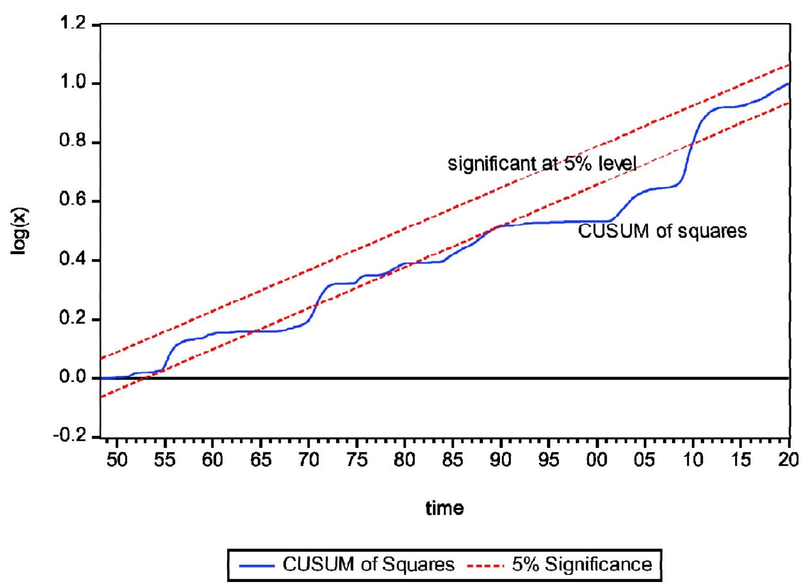


Figure 2: Stability test

Source: Plotted by author.

Stability test of the estimated trend line was done through CUSUM of squares test where the test was not significant at 5% level during 1964-1970 and 1990-2009 respectively otherwise it is significant.

The polynomial trend of US unemployment level is fully cyclical where estimated or smooth cyclical trend contains clearly 7 peaks and 6 troughs respectively in comparison with the actual level of unemployment during the monthly data 1948 – 2020 which are depicted in Figure 3 below. The duration of declining unemployment took longer time than rising trend in most of the cycles.

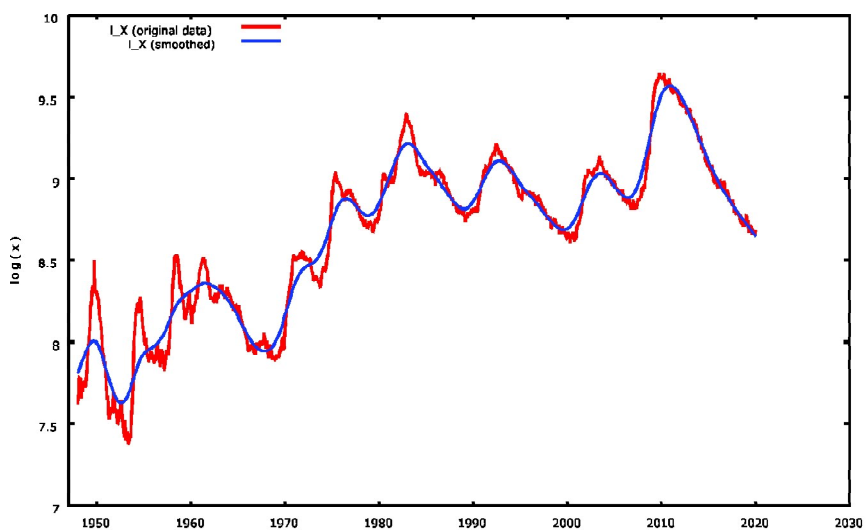


Figure 3: Polynomial trend

Source: Plotted by author

Forecast series of US unemployment level up till 2030 contains cyclical trends of two peaks and one trough from 2020 to 2030 in the monthly data which are significant at 5% level showing shaded region with blue trend line which is more or less increasing patterns where log(x) at 1948:01=7.667744, at 2020:01=8.64261 and at 2030:01=8.732872 respectively. In Figure 4, all the peaks and troughs during 1948 to 2030 have been clearly drawn.

Hodrick-Prescott Filter model (1997) decomposed US unemployment level into trend and cycles using monthly data from 1948m_1 to 2020m_1 taking $\lambda = 14400$ where it was found that in the cycles the series contains numerous troughs and peaks but in the smooth trend it consists of only 7 peaks and 6 troughs after estimation which is clearly observed in Figure 5.

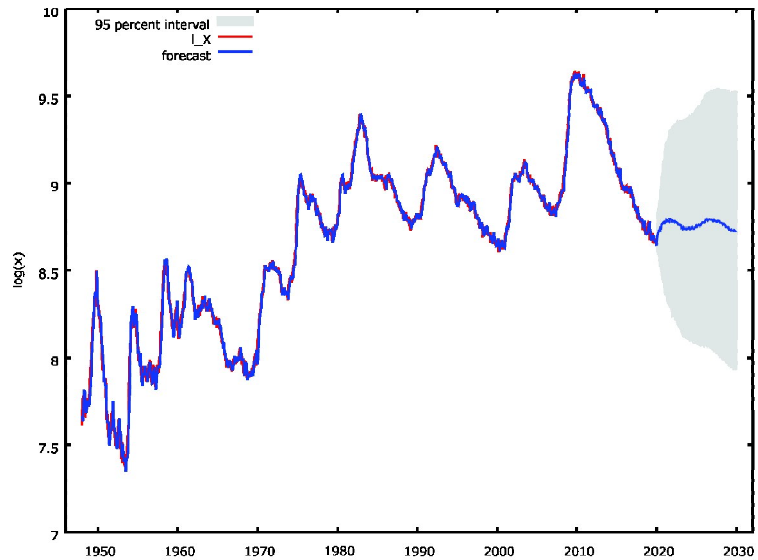


Figure 4: Prediction of US employment

Source: Plotted by author

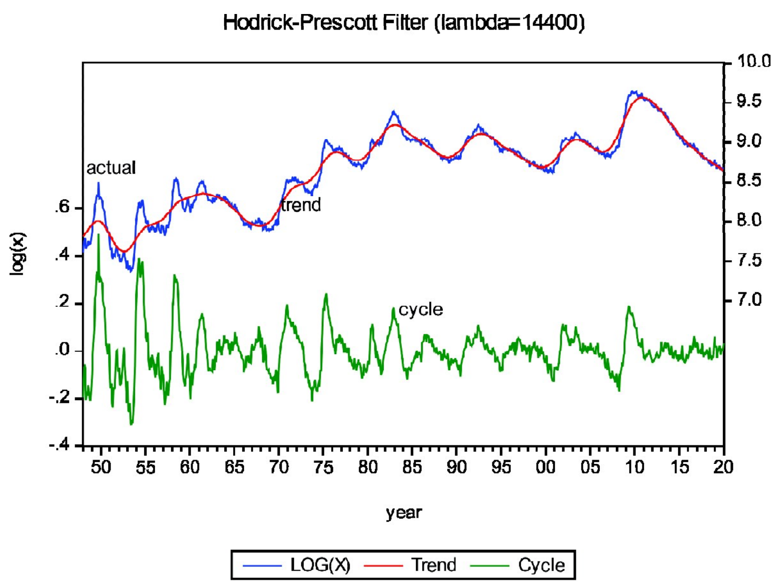


Figure 5: H. P. Filter model

Source: Plotted by author.

But, the cyclical variations both in the cycle and in the trend vanished in the first differenced log series of US unemployment level in the monthly data during $1948m_1$-$2020m_1$ since as λ tends to infinity the trend line approaches to linearity which is visible in the Figure 6 where red line tends to zero and cycles moves around zero and the cyclical variations reduced as time goes on which indicates that its volatility diminishes.

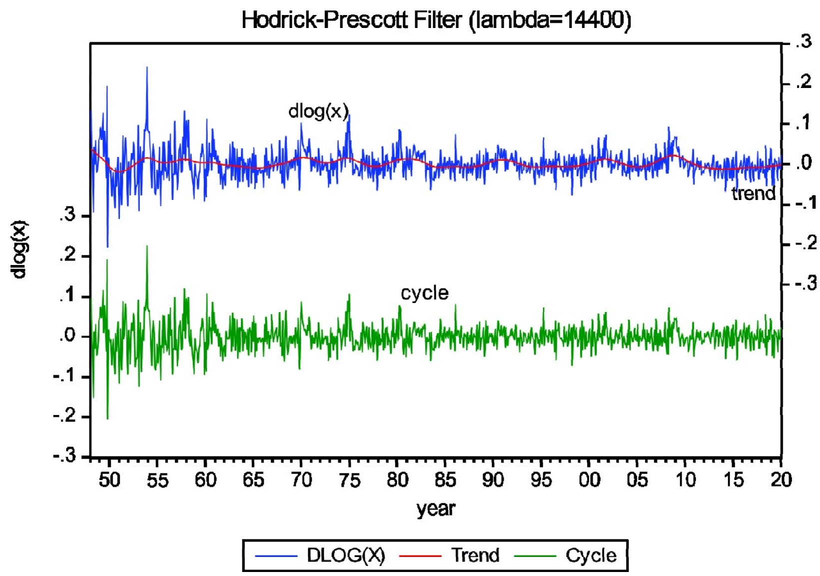


Figure 6 : Approximately linear trend

Source: Plotted by author

Hodrick (2020) cited Morley et al. (2003) when ARIMA model was used in GDP series of US in analysing the decomposition of the trends and cycles. It has inspired us to detect the best fitted ARIMA(p, d, q) model of US unemployment level from the monthly data during 1948m_1 to 2020m_1. Among the best 12 models, the ARIMA (4, 1, 4) was selected for analysis of equilibrium.

Using exact maximum likelihood method, the estimated ARIMA(4, 1, 4) of us unemployment has been observed as given below.

$$dlog(x_t)=0.\ 001397+0.\ 5405dlogx_{t-1}+0.\ 1469dlogx_{t-2}+0.\ 6953dlogx_{t-3}-0.\ 7126dlogx_{t-4}$$
$$(0.\ 66) \quad (9.\ 86)^* \quad (3.\ 08)^* \quad (14.\ 33)^* \quad (-13.\ 34)^*$$

$$+\,\text{€}_t-0.\ 5226\,\text{€}_{t-1}+0.\ 0245\text{€}_{t-2}-0.\ 6717\text{€}_{t-3}+0.\ 7501\text{€}_{t-4}$$
$$(-9.\ 63)^* \quad (0.\ 62) \quad (-15.\ 02)^* \quad (12.\ 04)^*$$

SIC=-3275. 890, AIC=-3323. 505, AR roots=1. 0844±0. 3669i, -0. 5965±0. 8456i

MA root=1. 0124±0. 4930, -0. 5647±0. 6659i, *=significant at 5% level. Observations=864

It was found that all the coefficients of AR and MA are significant except one and values are less than one and even some roots of AR(4) and MA(4) do not lie inside the unit circle which showed that the model is unstable and nonstationary. Moreover, SIC and AIC are minimised.

This ARIMA (4, 1, 4) has been used to forecast at 2030 where dlog(x) at 1948:2=0. 011316 and dlog(x) at 2030:1=0. 037730 and the unemployment series of dlog(x) has been approaching towards equilibrium which indicates that the model is converging since z values of coefficients are significant at 5% level. In Figure 7, the change of unemployment ARIMA(4, 1, 4) in forecasting to 2030 is depicted clearly. The shaded region showed the forecasting period which was also significant at 5% level. The red line indicates the actual and the blue line is the estimated forecasting series up to 2030.

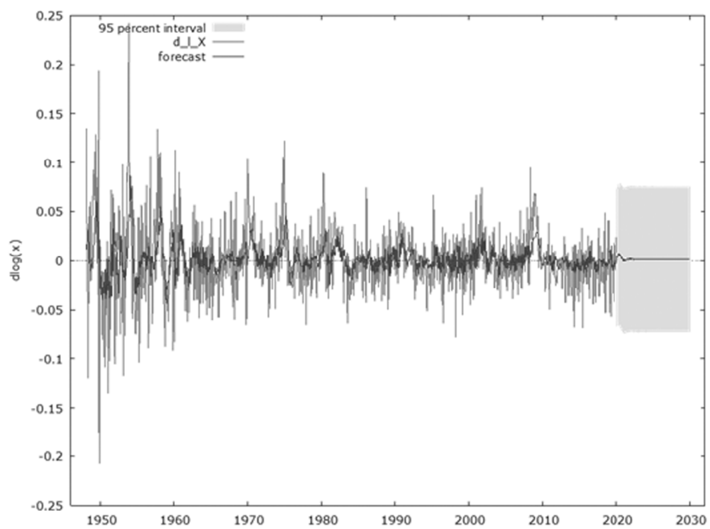


Figure 7: Convergent ARIMA(4, 1, 4) for 2030

Source: Plotted by author.

Impulse response function of ARIMA (4, 1, 4) of dlog(x) has been obtained and it indicates that one standard deviation innovation resulted the change of unemployment level of USA from 1948 to 2030 moves towards equilibrium assuming the impulse response function is bounded with ±standard errors. In Figure 8, it is plotted.

(ii) Seasonal variation of US unemployment

In the AR process, the estimate of the AR(12) of the log of unemployment level of USA in the monthly data during $1948m_1$-$2020m_1$ is given below.

$$\text{Log}(x)_t = 8.554 + 0.919\log(x)_{t-12} + 0.042\sigma^2_t$$
$$(111.\ 63)^* \qquad (71.\ 07)^* \qquad (22.\ 57)^*$$

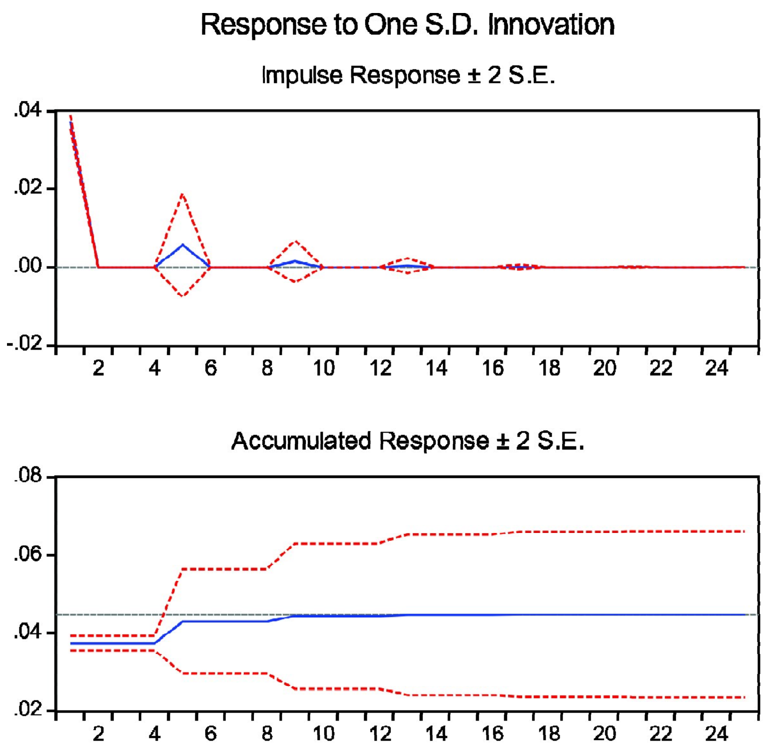


Figure 8: Impulse Response Function

Source: Plotted by author

$$R^2 = 0.83,\ F = 2116.18,\ DW = 0.07,\ \text{AR roots} = \pm 0.99,\ 0.86 \pm 0.50i,\ -0.86 \pm 0.50i,\ -0.00 \pm 0.99i,\ 0.50 \pm 0.86i,$$

$$ACF_{12} = -0.03,\ ACF_{24} = -0.09,\ ACF_{36} = -0.11,\ \text{and } PACF_{12} = -0.11,\ PACF_{24} = -0.07,\ PACF_{36} = 0.054$$

The AR(12) model is significant, stable and stationary since, coefficients are significant, roots are less than one. The significant patterns of ACF and PACF confirm the seasonality in which volatility was minimised through σ^2.

In the Table 2, autocorrelation functions and partial autocorrelation functions with their Q statistics and their probabilities upto lag 36 have been shown for cross checking.

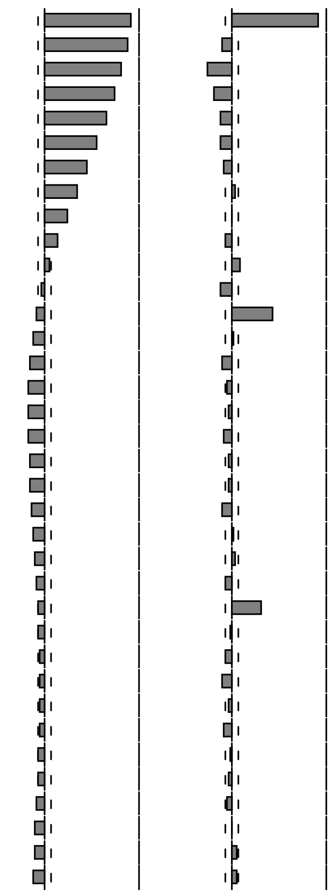
Likewise, the MA (12) process of log unemployment level of USA during 1948-2020 is estimated below.

$$\text{Log}(x)_t = 8.658 + 0.784€_{t-12} + 0.1059\sigma^2_t$$
$$(386.44)^* \quad (37.43)^* \quad (19.07)^*$$

Table 2
ACF and PACF of AR(12) of us unemployment during 1948m_1-2020m_1

Date: 05/10/20 Time: 13:28
Sample: 1948M01 2020M01
Included observations: 865
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation Partial Correlation



	AC	PAC	Q-Stat	Prob
1	0.960	0.960	799.27	
2	0.913	-0.10...	1523.3	0.000
3	0.846	-0.27...	2146.2	0.000
4	0.765	-0.20...	2655.9	0.000
5	0.673	-0.13...	3050.8	0.000
6	0.570	-0.13...	3334.4	0.000
7	0.461	-0.09...	3520.0	0.000
8	0.355	0.033	3630.2	0.000
9	0.250	-0.00...	3685.0	0.000
1...	0.145	-0.08...	3703.6	0.000
1...	0.055	0.089	3706.2	0.000
1...	-0.03...	-0.11...	3707.4	0.000
1...	-0.08...	0.448	3714.1	0.000
1...	-0.12...	0.013	3728.7	0.000
1...	-0.16...	-0.10...	3751.3	0.000
1...	-0.17...	-0.05...	3779.0	0.000
1...	-0.18...	-0.03...	3808.6	0.000
1...	-0.18...	-0.08...	3837.6	0.000
1...	-0.16...	-0.02...	3862.9	0.000
2...	-0.15...	-0.04...	3884.7	0.000
2...	-0.14...	-0.11...	3903.5	0.000
2...	-0.12...	0.012	3917.6	0.000
2...	-0.11...	0.033	3928.7	0.000
2...	-0.09...	-0.07...	3936.7	0.000
2...	-0.07...	0.328	3942.0	0.000
2...	-0.06...	-0.02...	3945.9	0.000
2...	-0.05...	-0.08...	3948.6	0.000
2...	-0.05...	-0.10...	3950.9	0.000
2...	-0.05...	-0.03...	3953.4	0.000
3...	-0.05...	-0.09...	3956.4	0.000
3...	-0.06...	-0.02...	3960.4	0.000
3...	-0.07...	-0.02...	3965.9	0.000
3...	-0.08...	-0.05...	3972.7	0.000
3...	-0.10...	0.006	3981.6	0.000
3...	-0.11...	0.050	3992.8	0.000
3...	-0.11...	0.054	4005.1	0.000

Source: Calculated by author

$R^2 = 0.57$, F = 584.60*, DW = 0.040, *=significant at 5% level

MA roots = 0.95 ± 0.25i. 0.69 ± 0.69i, 0.25 ± 0.95i, –0.69 ± 0.69i, –0.95 ± 0.25i

$ACF_{12} = 0.453$, $ACF_{24} = 0.747$, $ACF_{36} = 0.421$, $PACF_{12} = –0.03$, $PACF_{24} = –0.01$, $PACF_{36} = 0.061$

Both ACF and PACF have been decreasing and then increasing. Besides after lag 24, ACF rises and PACF decline. There is a single spike at lag 13.

The estimated model is significant, stable and stationary because MA roots are less than one. The ACF did not confirm seasonality although PACF confirmed seasonality where σ^2 is minimised.

In Table 3, MA(12) process of US unemployment has been shown clearly.

Table 3
MA(12) of US unemployment

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.976	0.976	827.17	
		2	0.948	-0.09...	1609.0	0.000
		3	0.909	-0.25...	2328.2	0.000
		4	0.864	-0.11...	2978.9	0.000
		5	0.811	-0.13...	3553.2	0.000
		6	0.751	-0.14...	4045.9	0.000
		7	0.689	0.002	4461.4	0.000
		8	0.633	0.163	4811.6	0.000
		9	0.581	0.129	5106.9	0.000
		1...	0.530	-0.01...	5353.6	0.000
		1...	0.490	0.155	5564.8	0.000
		1...	0.453	-0.03...	5745.5	0.000
		1...	0.452	0.698	5925.3	0.000
		1...	0.456	0.037	6108.2	0.000
		1...	0.469	-0.06...	6302.4	0.000
		1...	0.489	-0.06...	6513.8	0.000
		1...	0.518	-0.06...	6750.8	0.000
		1...	0.554	-0.01...	7022.8	0.000
		1...	0.594	-0.01...	7335.5	0.000
		2...	0.631	-0.00...	7688.6	0.000
		2...	0.663	-0.07...	8079.5	0.000
		2...	0.698	0.057	8512.9	0.000
		2...	0.724	-0.01...	8979.3	0.000
		2...	0.747	-0.01...	9476.7	0.000
		2...	0.745	0.048	9971.7	0.000
		2...	0.738	0.046	10459.	0.000
		2...	0.724	0.020	10927.	0.000
		2...	0.703	-0.00...	11370.	0.000
		2...	0.675	0.014	11778.	0.000
		3...	0.638	-0.04...	12144.	0.000
		3...	0.598	0.004	12466.	0.000
		3...	0.559	-0.02...	12747.	0.000
		3...	0.523	-0.03...	12994.	0.000
		3...	0.484	0.037	13205.	0.000
		3...	0.451	-0.04...	13389.	0.000
		3...	0.421	0.061	13549.	0.000

Source: Calculated by author

But the estimated integratedARIMA (12, 0, 12) model is observed as,

$$\underset{}{\mathrm{Log}(x)_t} = \underset{(104.60)^*}{8.557} + \underset{(59.60)^*}{0.9149}\log(x)_{t-12} + \epsilon_t + \underset{(0.918)}{0.0302}\epsilon_{t-12} + \underset{(27.19)^*}{0.042}\sigma^2_t$$

$R^2 = 0.83$, F = 1410.16*, DW = 0.077, AR roots = ±0.91, 0.86 ± 0.50i, 0.50 ± 0.86i, 0.00 ± 0.99i, –0.50 ± 0.86i, –0.86 ± 0.50i, MA roots = 0.72 ± 0.19i, 0.53 ± 0.53i, 0.19 ± 0.72i, –0.19 ± 0.72i, –0.53 ± 0.53i, –0.72 ± 0.19i

This model is stable but convergent insignificantly because coefficient of MA(12) is not significant.

ACF and PACF confirm seasonality and ACF has a single spike and PACF has three. $ACF_{12} = –0.06$, $ACF_{24} = –0.08$, $ACF_{36} = –0.11$, $PACF_{12} = –0.12$, $PACF_{24}$ = -0.07, $PACF_{36} = 0.053$. So that after lag 24, all ACF are negative and PACF are both positive and negative. All these ACF and PACF are significant in Q statistic at 5% significant level.

The integrated ARIMA (12, 0, 12) of US unemployment during $1948m_1$-$2020m_1$ has been shown in details with ACF, PACF, Q statistic and probabilities in Table 4.

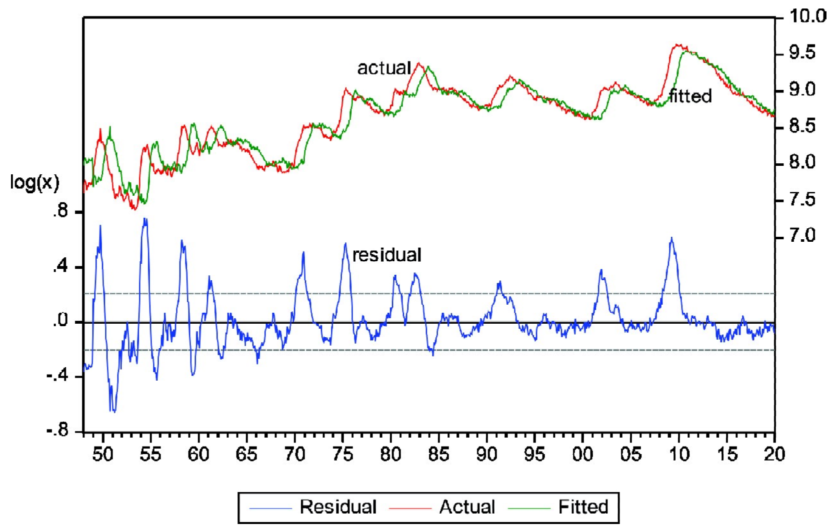
Table 4
ARIMA (12, 0, 12) of us unemployment

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.959	0.959	797.65	
		2	0.911	-0.10...	1518.3	
		3	0.842	-0.27...	2135.4	0.000
		4	0.759	-0.20...	2637.0	0.000
		5	0.664	-0.13...	3021.9	0.000
		6	0.559	-0.13...	3294.4	0.000
		7	0.447	-0.09...	3469.0	0.000
		8	0.338	0.034	3569.3	0.000
		9	0.232	-0.00...	3616.2	0.000
		1...	0.125	-0.08...	3629.9	0.000
		1...	0.033	0.088	3630.9	0.000
		1...	-0.06...	-0.12...	3634.0	0.000
		1...	-0.10...	0.460	3644.4	0.000
		1...	-0.14...	0.013	3664.0	0.000
		1...	-0.17...	-0.11...	3692.1	0.000
		1...	-0.19...	-0.05...	3725.0	0.000
		1...	-0.19...	-0.03...	3758.8	0.000
		1...	-0.19...	-0.08...	3791.0	0.000
		1...	-0.17...	-0.03...	3818.1	0.000
		2...	-0.15...	-0.04...	3840.6	0.000
		2...	-0.14...	-0.11...	3859.2	0.000
		2...	-0.12...	0.011	3872.4	0.000
		2...	-0.10...	0.035	3882.0	0.000
		2...	-0.08...	-0.07...	3888.4	0.000
		2...	-0.06...	0.332	3892.3	0.000
		2...	-0.05...	-0.02...	3894.8	0.000
		2...	-0.04...	-0.08...	3896.4	0.000
		2...	-0.03...	-0.10...	3897.7	0.000
		2...	-0.04...	-0.03...	3899.1	0.000
		3...	-0.04...	-0.09...	3900.9	0.000
		3...	-0.05...	-0.01...	3903.7	0.000
		3...	-0.06...	-0.03...	3907.9	0.000
		3...	-0.07...	-0.05...	3913.4	0.000
		3...	-0.09...	0.005	3921.2	0.000
		3...	-0.10...	0.051	3931.3	0.000
		3...	-0.11...	0.053	3942.8	0.000

Source: Calculated by author

The estimated ARIMA(12, 0, 12) has been drawn in Figure 9.

Figure 9: ARIMA(12, 0, 12)



Source: Plotted by author.

ARIMA (12, 0, 12) suffers from heteroscedasticity problem which was verified through heteroscedasticity test applying ARCH process taking lag 12 and the estimated equation is given below.

$$\epsilon^2_t = 0.00318 + 0963\epsilon^2_{t-1} + 0.1304\epsilon^2_{t-2} - 0.024\epsilon^2_{t-3} - 0.2118\epsilon^2_{t-4} + 0.093\epsilon^2_{t-5} - 0.073\epsilon^2_{t-6}$$
$$(2.01)^* \quad (28.05)^* \quad (2.73)^* \quad (-0.508) \quad (-4.43)^* \quad (1.93)^* \quad (-1.51)$$

$$+ 0.003\epsilon^2_{t-7} - 0.071\epsilon^2_{t-8} + 0.069\epsilon^2_{t-9} + 0.056\,\epsilon^2_{t-10} - 0.106\epsilon^2_{t-11} + 0.0914\epsilon^2_{t-12}$$
$$(0.06) \quad (-1.47) \quad (1.44) \quad (1.17) \quad (-2.22)^* \quad (2.67)^*$$

$R^2 = 0.879$, $F = 511.54^*$, $DW = 1.96$, $nR^2 = 750.325$ which is significant at 5% level at $\chi^2(12)$ test.

At null hypothesis no heteroscedasticity is rejected since probability is 0. 00.

Thus GARCH (1, 1) model is chosen for dlog(x) during $1948m_1$-$2020m_1$ to show high volatility where z values of both the coefficients are significant at 5% level and they are less than one showing convergent which was verified by the conditional variance.

$$h_t = 4.18E{-}05 + 0.1139\epsilon^2_{t-1} + 0.849h_{t-1}$$
$$(3.15)^* \quad (5.42)^* \quad (31.11)^*$$

$R^2 = -0.0065$, $DW = 1.74$, $AIC = -3.99$, $SC = -3.97$, $HQ = -3.98$, *=significant at 5% level.

The Conditional variance is steadily falling downward but without reaching zero which indicates that it is still nonstationary however volatility have been reducing.

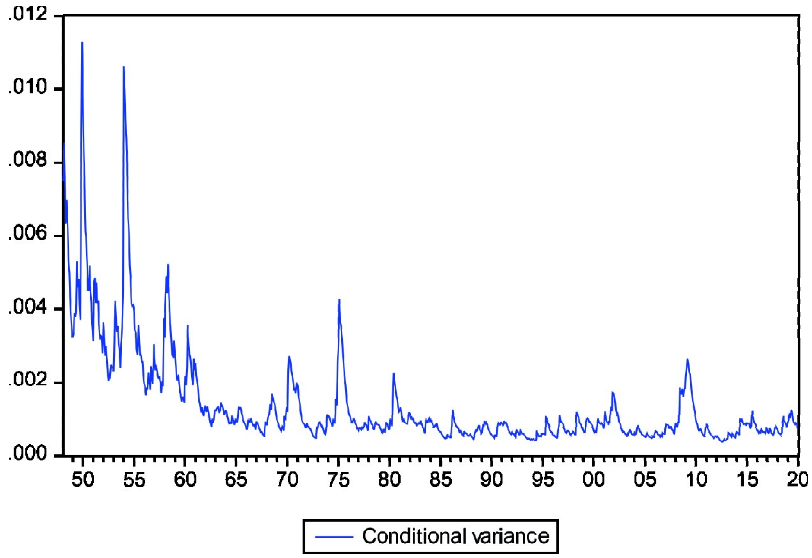


Figure 10: Conditional variance of GARCH

Source: Plotted by author

The decomposition of actual monthly unemployment level of USA during $1948m_1$-$2020m_1$ from seasonality, trend and seasonal adjustment components have been done through STL method and are given by panels of Figure 11 below where panel(1) showed actual series of US unemployment containing many upward and downward cycles, panel (2) contains trend series of unemployment which looks like the actual one , panel(3) verified the seasonal variation which consists of many volatilities and huge fluctuations, panel (5) showed adjusted seasonality which differs marginally with trend and actual.

The merger of trend, actual and seasonally adjusted unemployment of US monthly data from 1948-2020 has been depicted showing spikes in Figure 12 and is given below while it is observed that the deviation from actual seasonally adjusted and trend data are marginal.

In the next panel diagram interpreted the significant changes of monthly variation of seasonality of US unemployment from January to December respectively. Panel(1) clarified seasonal variation of monthly unemployment of USA, panel(2) verified the seasonally adjusted monthly unemployment level and panel(3) showed the trend sequence of seasonal monthly unemployment level where no abnormal variabilities were observed as a whole.

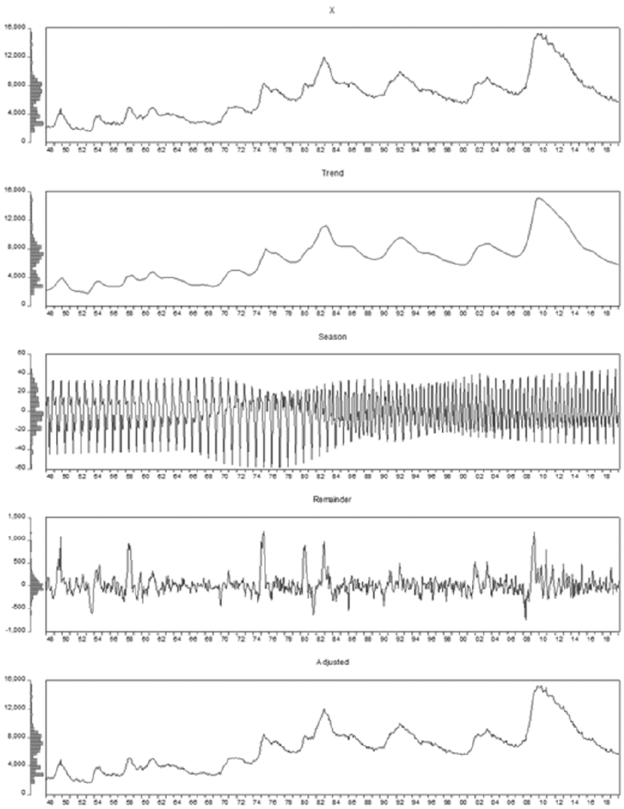


Figure 11 : Decomposition

Source: Plotted by author.

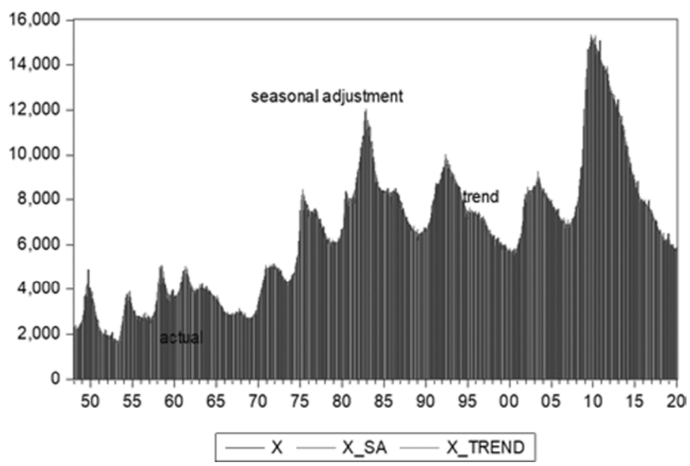


Figure 12: Composite figure

Source: Plotted by author

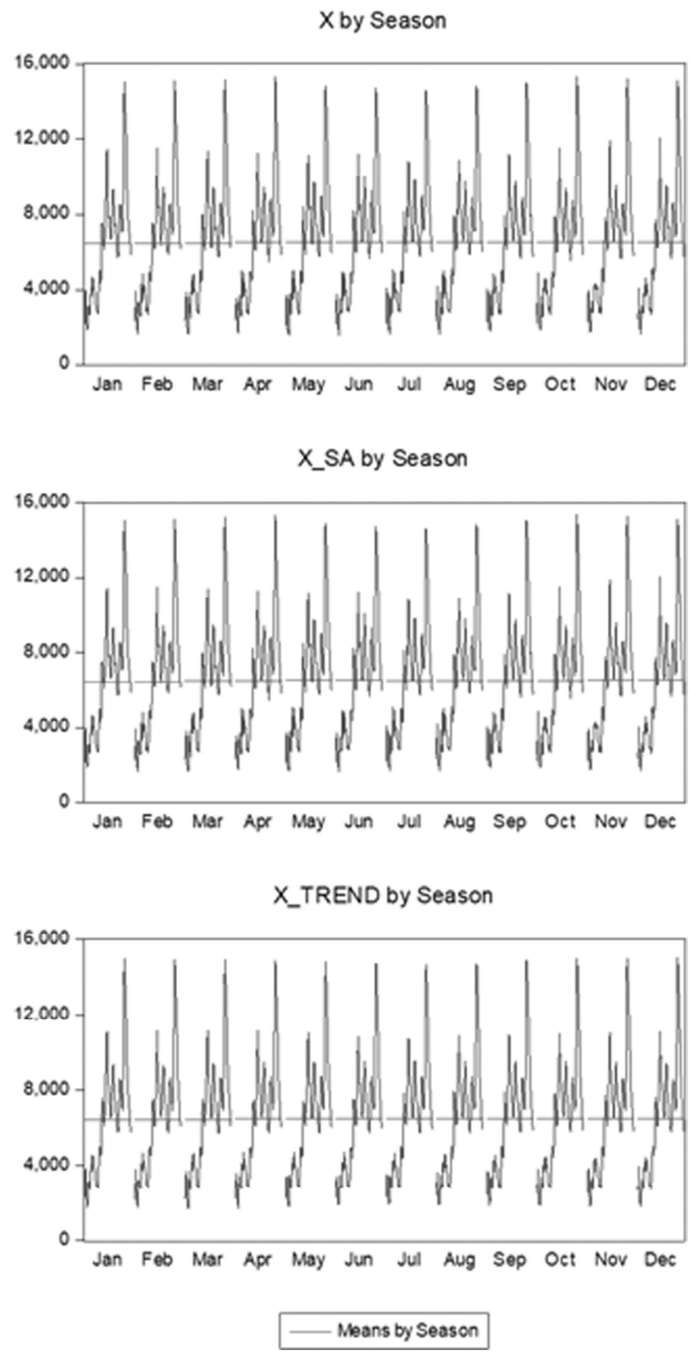


Figure 13: Seasonal decomposition

Source: Plotted by author.

It implies that the seasonal difference approaches equilibrium or it tends to minimisation of variability so that change of seasonal fluctuation of US monthly unemployment vanishes towards zero which is clearly visible in the figure 14.

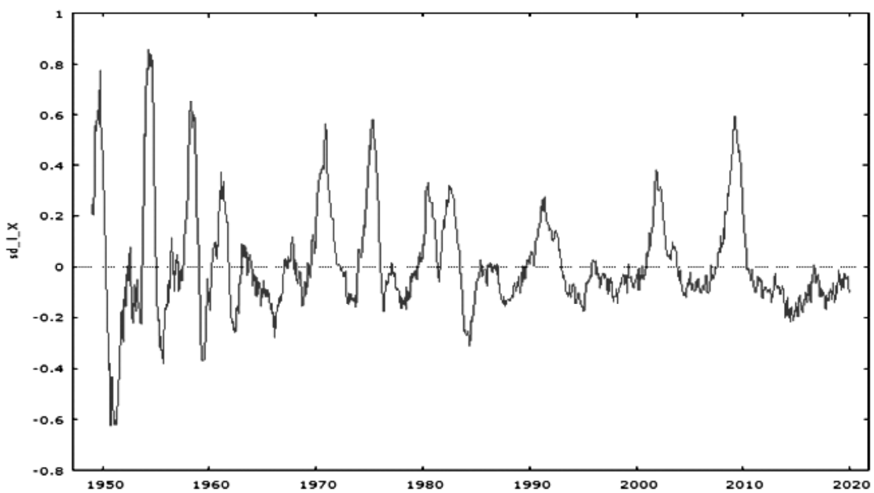


Figure 14: Seasonal difference

Source: Plotted by author.

V. LIMITATIONS AND FUTURE SCOPE OF RESEARCH

The main shortcoming of the analysis is that it avoids to state the permanent and transitory components of the cycles. The non-stationarity could not be avoided in the first difference series in the ARIMA models. The paper should have enough scope for future research in the monthly seasonal variation of unemployment. Even, the paper should calculate the equilibrium unemployment in the cyclical and trend component under H. P. Filter model during the specified monthly data of US unemployment level.

VI. CONCLUSION

The paper concludes that the unemployment level of USA during $1948m_1$-$2020m_1$ is cyclical and in cubic trend it is estimated as concave upward. H. P. Filter model constitutes smooth cycles with seven peaks and 6 troughs with many volatile cycles in which volatility slowly reduced and tended to zero as observed from the first difference series of unemployment level. The fitted ARIMA(4, 1, 4) is selected as forecast model which showed stability of volatility and tends to equilibrium at 2030 in which impulse response function also moves to equilibrium.

The ARIMA(12, 0, 12) of the level series of US unemployment confirmed the seasonal patterns in autocorrelation and partial autocorrelation functions in which the model also contains heteroscedasticity and GARCH(1, 1) verified the nature of volatility where conditional variance proved the declining volatility. The trends and cycles were decomposed where seasonal variations during 1948m_1-2020m_1 and the monthly volatility from January to December was assured wide ranging seasonality and trend, actual and seasonal adjustment were found marginal differences and was observed as like as superimposed cyclical curves.

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