A new unit root analysis for testing hysteresis in unemployment

Yaya, OlaOluwa S and Ogbonna, Ephraim A and Furuoka, Fumitaka and Gil-Alana, Luis A.

Economic and Financial Statistics, Department of Statistics, University of Ibadan, Nigeria, Economic and Financial Statistics, Department of Statistics, University of Ibadan, Nigeria Centre for Econometric and Allied Research, University of Ibadan, Nigeria, Asia–Europe Institute, University of Malaya, Malaysia, Faculty of Economics, University of Navarra, Pamplona, Spain and Facultad de C. Juridicas y Empresariales, Universidad Francisco de Vitoria, Madrid, Spain

19 October 2019

A new unit root analysis for testing hysteresis in unemployment[1]

OlaOluwa Simon Yaya
Economic and Financial Statistics, Department of Statistics, University of Ibadan, Nigeria
Email: os.yaya@ui.edu.ng; o.s.olaoluwa@gmail.com

Ahamuefula E. Ogbonna
Economic and Financial Statistics, Department of Statistics, University of Ibadan, Nigeria &
Centre for Econometric and Allied Research, University of Ibadan, Nigeria.
Email address: ae.ogbonna@cear.org.ng; ogbonnaephraim@gmail.com

Fumitaka Furuoka
Asia–Europe Institute, University of Malaya, Malaysia
Email: fumitaka@um.edu.my; fumitakamy@gmail.com

Luis Alberiko Gil-Alana
Faculty of Economics, University of Navarra, Pamplona, Spain and
Facultad de C. Juridicas y Empresariales, Universidad Francisco de Vitoria, Madrid, Spain
Email: alana@unav.es

Abstract

This paper proposes a nonlinear unit root test based on the artificial neural network-augmented Dickey-Fuller (ANN-ADF) test for testing hysteresis in unemployment. In this new unit root test, the linear, quadratic and cubic components of the neural network process are used to capture the nonlinearity in the time-series data. Fractional integration methods, based on linear and nonlinear trends are also used in the paper. By considering five European countries such as France, Italy, Netherland, Sweden, and the United Kingdom, the empirical findings indicate that there is still hysteresis in these countries. Among batteries of unit root tests applied, both the ARNN-ADF and fractional integration tests fail to reject the hypothesis of unemployment hysteresis in all the countries.

Keywords: Unit root process; Nonlinearity; Neuron network: Time-series; Hysteresis; Unemployment; Europe; Labour market.

JEL Classification: C22, E24.

[1] The analysis was conducted using the Ox program and the EViews statistical software. The author is grateful to Professor Jurgen A. Doornik for providing OxEdit free of charge for academic purposes. The data and OxGauss codes are available at: https://sites.google.com/site/fumitakafuruokaswebpage/data-and-oxgauss-codes-iii/paper-39 and EViews codes at https://sites.google.com/site/fumitakafuruokawebpage2/home/paper-11. Fractional integration analyses were conducted using Fortran programming language, and the code is available from authors on request. Luis A. Gil-Alana gratefully acknowledges financial support from the Ministerio de Ciencia y Tecnología ((ECO2017-85503-R) and also from an internal project from the Universidad Francisco de Vitoria.

1. Introduction

The need for a new unit root test based on Autoregressive Neural Network (ARNN) nonlinearity is imperative since the evolution of the Neural Network (NN) process. Note that this process is slightly different from an AR process, and the process has gained its popularity due to its ability to approximate almost any nonlinear function arbitrarily close (Franses and van Dijk, 2003). When the ARNN model is applied to a time series that is characterized by nonlinearity, the model will detect this nonlinearity and provide a superior fit compared to the linear AR model. Noting that the Augmented Dickey-Fuller (ADF) unit root test of Dickey and Fuller (1979) is based on an AR process of order p, and many unit root tests for linearity and nonlinearity are based on this model foundation, there is the need to have an ARNN-unbiased unit root test, upon which unit root testing on NN-based series will be based, similar to ADF test. The Kapetanios, Snell and Shin (KSS, 2003) unit root test, for example, is based on the Exponential Smooth Transition Autoregression (ESTAR) nonlinearity, and quite a number of theoretical and empirical applications have accepted this unit root test as standard nonlinear AR unit root test for testing unit roots in nonlinear frameworks on economic and financial datasets majorly.

The application areas of NN models are enormous; they are found being applied in psychology, computer science, engineering, linguistics, and economics and finance. The model mimics the neural structure of the brain, and this makes it useful for studying pattern recognition, classification and nonlinear features in the datasets. The ARNN is a kind of NN model with an AR specification, which is a more general NN model. The ability of the model to approximate any Borel-measurable function further makes the model an appealing choice to researchers (see Hornik, Stinchcombe and White, 1989; Rech, 2002). Based on impressive successes of NN in modelling nonlinearity in time series, there is a need to obtain a tailored unit root test towards NN realizations since KSS and ADF unit root applications are biased towards NN realizations.

Time series are mostly characterized by non-linearity (see, e.g., Tiao and Tsay, 1994; Stanca, 1999) and as such, the applications of most extant econometric models (the ARIMA-based models)[2], which impose the linearity assumptions on the examined series, are however limited. The imposition leads to a misspecification of the data generating process that produces the time series, and as a consequence, the estimates and forecasts emanating from such models may be grossly misleading (see Binner et al. 2005; Teräsvirta, 2005, among others). This has however led to the development of several other nonlinear models, such as the bilinear model, the exponential autoregressive model, the threshold autoregressive model, the autoregressive conditional heteroscedasticity model and its variants, the smooth transition autoregressive model, the non-linear autoregressive model, the non-linear moving average model, wavelet networks, and artificial neural networks, among others (Haggan and Ozaki, 1981; Tong, 1990; Escribano and Jorda, 1999; Engle, 2003; van Dijk et al., 2004; Robinson, 2005; Terasvirta, 2005; De Gooijer and Hyndman, 2006; Iacus, 2011; etc.), in a bid to account for the inherent non-linearity. However, the plausibility of diverse functional forms of non-linearity still poses a problem to the development of non-linear models (see Binner et al. 2005), as these models are not able to accommodate the divergent non-linear patterns that are, often simultaneously, present in the series. Thus, more robust models that adequately account for the inherent non-linearity, regardless of the diverse functional form, is required.

The neural networks, in contrast with extant linear econometric models and other non-linear models, therefore provides a better and more flexible framework. It accurately produces non-linear models that account for inherent non-linearity, as well as the plausibility of diverse non-linear functional forms (Hornik et al., 1989), given that it is data-driven and independent

[2] The Autoregressive Integrated Moving Average model.

of the prior beliefs about the functional form. While some studies have empirically compared the performance of linear econometric models with the non-linear neural networks, there seemed not to be any established consistency in the superiority of the latter over the former (see Johnes, 2000; Moshiri and Cameron, 2000; among others). As an immediate consequence, the appropriateness of the implementation of the neural networks to generate accurate results was queried (Adya and Callopy, 1998), giving rise to the development of some basic guidelines (Gorr et al., 1994; Balkin and Ord, 2000; etc.). The significance and power of NN processes are greatly reduced whenever the subjectivity in determining the number of required training units is not adequately minimized (see Moshiri and Cameron, 2000; Nag and Mitra, 2002; among many others). However, in a bid to improve the model precision, other variants of the neural networks have been developed, and these include the neural network Nonlinear Autoregressive Moving Average (NARMA) and higher-order autoregressive neural network (Connor and Martin, 1994; Burges and Refenes, 1999; etc.). However, these variants are found not to completely capture the non-linearity especially when time series has a moving average component, and a deep learning neural network with or without hybrid methodologies such as fuzzy logic has also been suggested, for example, in Tealab et al. (2017).

Conventional unit root tests (ADF, PP, KPSS, etc.) in extant literature were mostly developed based on the linearity assumption, given the wide adoption of the econometric models that impose linearity on the series. However, as pointed out earlier, it is not quite unexpected that most macroeconomic series exhibit non-linear patterns, a limiting factor to the efficiency of econometric models. Therefore, adopting the conventional unit root tests in a framework that is already characterized by non-linearity would definitely be inappropriate. This is largely because the conventional unit root tests, as originally designed, do not account for the non-linearity and presence of structural breaks, and this reduces their power to reject the null of a unit root. Other linear unit root tests that accommodate the presence of structural breaks exist in the literature, such as the prominent Lagrange Multiplier (LM) unit root test (Lee and Strazicich, 2013). However, the linear unit root test variants only account for the non-linearity occasioned by the presence of structural breaks (Taylor, 2002). Hence, these conventional unit root tests fail to accommodate simultaneously the divergent non-linear patterns that may be inherent in the data, thus leading to incorrect conclusions on the stationarity, or non-stationarity, of the examined time series data, especially one that was generated from a non-linear DGP (see Van Dijk et al., 2002; Franchi and Ordonez, 2008; among others). In a panel structure, several unit root testing frameworks are repleted in the literature and have been categorized into two sub-groups – the first and second generation panel unit root tests, while the first generation panel unit root tests – the LLC test (Levin et al., 2002), IPS test (Im et al., 2003) and MW test (Maddala and Wu, 1999) assume no cross-dependence among the variables. The second generation – the CH test (Choi, 2002), MP test (Moon and Perron, 2004) and Pesaran (2007) test, among others, allow for cross-dependence. Some studies (Camarero and Tamarit, 2004; Camarero et al., 2006; etc.), however, found plausible cross-dependences between or among examined time series, which informed the development of the panel unit root tests that adequately account for these cross-dependences (Taylor and Sarno, 1998; Maddala and Wu, 1999; Levin et al., 2002; Im et al., 2003; Pesaran, 2007; etc.). Often times, the stationarity stance of the different unit root tests are contradictory, thus requiring the practice of employing a battery of unit root tests (see Yaya, Ogbonna and Atoi, 2019; and Yaya, Ogbonna and Mudida, 2019: among others) to ascertain, with a higher precision, the stationarity, or non-stationarity, of a series. This practice shows the importance of capturing the inherent salient statistical features of any given data (see Salisu et al., 2018), which in this case, relates to the accounting for the divergent non-linear patterns. Studies that have attempted to incorporate non-linear dynamics into the unit root testing framework include Caner and Hansen (2001), Shin and Lee (2001), Kapetanios et al. (2003) among many others.

A review on unit root testing may be enormous (Choi, 2015) and these tests have been classified based on the underlying properties of the generating process. However, the NN-based unit root test is still lacking in the literature. This paper proposes a new ADF unit root test with artificial neural network nonlinearity in its specification of the test regression. The testing procedure is applied in testing hysteresis in several European unemployment rates. Our proposed unit root test contributes to the literature in NN modelling and forecasting. It also solves long overdue problems encountered during series transformation and stationarity tests of NN realized time series.

The rest of the paper is structured as follows: Following this introductory section, the second section explains the data and the research methodology, including a detailed explanation of the ARNN-ADF test procedure. The third section reports the empirical findings, while Section 4 concludes the paper.

2. Data and Statistical Approach

2.1. Data on the unemployment rate

Unemployment rates of five European countries, France (FR), Italy (IT), the Netherlands (NL), Sweden (SE) and the United Kingdom (UK) were retrieved from the Eurostat database (European Union, 2019). The series span between 1983 and 2018 covering 36 observations. The earliest unemployment data available is the year 1983 and, due to lack of sufficient long annual time-series on unemployment, some other major European economies, such as Belgium, Germany and Spain, are excluded from the empirical analysis.

2.2. Existing unit root analysis

There are numerous unit root tests which have been introduced and modified since the 1970s. These methods could be divided into the following three groups, namely the "first generation" unit root analysis, the "second generation", and the "third generation" unit root tests.

First of all, the first generation of unit root tests, namely the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979, 1981), the Phillips-Perron (PP) test (Phillips and Perron, 1988), and the Dickey-Fuller test with GLS detrending (DF-GLS) test (Elliott *et al.*, 1996), are standard and they have been well-established in the 1980s and 1990s. They have also been incorporated in major econometric software, such as EViews, Stata and RATS. The ADF test is based on the following equation:

$$(1-L)\,y_t = \mu + \beta t + \rho\, y_{t-1} + \sum_{i=1}^{p} c_i\,(1-L)\,y_{t-i} + \varepsilon_t, \qquad t = 1, 2, \ldots, \tag{1}$$

where y_t is the variable of interest, μ is a deterministic term, ε_t is the error term, β is the slope coefficient for the deterministic trend, t is deterministic time trend, ρ is the slope coefficient for the lagged dependent variable y_{t-1}, c is the slope coefficient for the lagged differenced dependent variable, and p is the lag length. The null and alternative hypotheses are given as,

$$H_0 : \rho = 0;\;\; H_A : \rho < 0; \tag{2}$$

testing the unit root in the time series against no unit root, respectively, which is computed using the usual t-statistic,

$$t_{ADF} = \frac{\hat{\rho}}{s.e.\left(\hat{\rho}\right)} \;. \tag{3}$$

where $\hat{\rho}$ is the estimate of ρ in the ADF regression model, and $s.e.\left(\hat{\rho}\right)$ is the estimated standard error of ρ. The PP test and the DF-GLS tests could be considered as a modified ADF test. In the PP test, the heteroskedastic and autocorrelation consistent (HAC) corrected variance is used to calculate the corresponding t-ratios (Phillips and Perron, 1988). In the DF-GLS test procedure, data are detrended by the generalized least squares (GLS) method (Elliott *et al.*, 1996).

The second generation of unit root tests, namely the ADF with structural breaks (ADF-SB) test (Perron and Vogelsang, 1992), the Fourier ADF (FADF) test (Enders and Lee, 2012) and the fractional integration (FI) analysis (Sowell, 1992, Robinson, 1994; Beran, 1995; etc.), are modified or defined versions of the first generation unit root analysis, developed to correct some shortcoming of the standard unit root tests. For example, the ADF-SB test could incorporate undefined structural breaks in the estimation model, the FADF test could take into account of unknown nonlinear terms in the analysis (Furuoka, 2017) and the fractional integration method could take into account of fractional integration (Robinson, 1994). The FADF test is based on the following equation:

$$(1 - L)\, y_t \;=\; \mu + \beta t + \gamma_1 \sin\left(\frac{2\pi k t}{T}\right) + \gamma_2 \cos\left(\frac{2\pi k t}{T}\right) + \rho\, y_{t-1} + \sum_{i=1}^{p} c_i\,(1-L)\, y_{t-i} + \varepsilon_t, \qquad (4)$$

where γ_1 and γ_2 measure, respectively, the amplitude and displacement of the sinusoidal component of the trigonometric function; k is the frequency in the Fourier approximation function and T is the number of observations. The Fourier function is used to capture the unknown nonlinearity in the time-series data. Furthermore, the ADF-SB test is based on the following equation:

$$(1 - L)\, y_t \;=\; \mu + \beta t + \delta DU_t + \theta D(T_B) + \rho\, y_{t-1} + \sum_{i=1}^{p} c_i\,(1-L)\, y_{t-i} + \varepsilon_t, \qquad (5)$$

where δ is the slope coefficient for the structural break dummy, $DU_t = 1$ if $t > T_B$ and $DU_t = 0$ otherwise, T_B is the breakpoint where the structural break occurs, θ is the slope coefficient for the one-time break dummy, $D(T_B)_t = 1$ if $t = T_B$ and $D(T_B)_t = 0$ otherwise. In this estimation method, two dummy variables, namely a structural break dummy and a one-time break dummy, are used to capture the undefined structural break.

Next, we describe the linear fractional unit root test which is the fractional equivalence of the ADF unit root test. In the fractional integration analysis, the number of differences required in the series may be any real value d, thus fractional. We consider both linear

(Robinson, 1994) and non-linear (Cuestas and Gil-Alana, 2016) set-ups based both on a regression model of the form:

$$y_t = f(\theta; t) + x_t; \qquad (1-L)^d x_t = u_t, \; t = 1, 2, ..., \tag{6}$$

where $f(\theta; t)$ maybe a linear or a nonlinear function. The u_t is supposed to be I(0) stationary. Note that the estimation of d in (6) is crucial in order to determine if the series is stationary (d < 0.5) or nonstationary (d ≥ 0.5), or if the shocks will have transitory (d < 1) or have permanent effects (d ≥ 1).

The third generation of unit root tests, namely the FADF with structural break (FADF-SB) test (Furuoka, 2017) and the Fourier fractional integration analysis (Gil-Alana and Yaya, 2018), are defined version of the second generation unit root analysis, developed to overcome some shortcoming of the existing unit root tests. For example, the FADF-SB test modified the FADF test by incorporating unknown structural breaks. The Fourier fractional integration analysis incorporates non-linearity in the analysis using the Fourier approximation method. The FADF-SB test is based on the following equation:

$$(1-L)\, y_t = \mu + \beta t + \gamma_1 \sin\left(\frac{2\pi k t}{T}\right) + \gamma_2 \cos\left(\frac{2\pi k t}{T}\right) + \delta DU_t + \theta D(T_B) + \rho\, y_{t-1} + \sum_{i=1}^{p} c_i\, (1-L)\, y_{t-i} + \varepsilon_t, \tag{7}$$

To test the unit root hypothesis, the *t*-statistic is used to test the null $\rho = 0$. In this FADF-SB test, the Fourier function is used to capture the unknown nonlinearity in the time-series data, and two break dummies are used to capture the undefined structural break.

By extending the FADF unit root test regression to the fractional unit root equivalent, we have the Fourier Fractional Integration model. For the Fourier fractional integration analysis, we remove some of the terms in the above equation, to allow for fractional differentiation, i.e.,

$$y_t = \mu + \beta t + \gamma_1 \sin\left(\frac{2\pi k t}{T}\right) + \gamma_2 \cos\left(\frac{2\pi k t}{T}\right) + x_t; \qquad (1-L)^d x_t = u_t, \; t = 1, 2, \ldots \tag{8}$$

2.3 ARNN-ADF testing procedure

The ARNN-ADF regression model is described in this section. To describe the testing regression, it is more convenient here to explain the ARNN model for a single hidden-layer model. The time series y_t is given as,

$$y_t = \phi_i' w_{1t} + \sum_{j=1}^{q} \theta_j F\left(\gamma_j' w_{2t}\right) + \varepsilon_t$$

$$y_t = \phi_i' w_t + \sum_{j=1}^{q} \theta_j F\left(\gamma_j' w_t\right) + \varepsilon_t \, , \tag{9}$$

where ϕ_i, $i = 1, 2, \ldots, p$ are the parameters of the linear AR(p) part of the model with $w_{1t} = \left(1, y_{t-1}, \ldots, y_{t-p}\right)$, $w_{2t} = \left(1, y_{t-1}, \ldots, y_{t-q}\right)$ and θ_j, $j = 1, 2, \ldots, q$ are the "connector strength" parameters. The function $F\left(.\right)$ is a bounded function called "hidden unit". The hidden unit function uses the logistic representation,

$$F\left(z\right) = \frac{1}{1 + \exp\left(-z\right)} \quad , \tag{10}$$

which takes values between 0 and 1, such that

$$F(\gamma_j^T w_t) = \frac{1}{1 + \exp(-\gamma_j^T w_t)} = \frac{1}{1 + \exp\left[-(\gamma_{11} y_{t-1} + \gamma_{12} y_{t-2} + \ldots + \gamma_{1k} y_{t-k} - c_1)\right]} \tag{11}$$

with $\gamma_1 = \left(\gamma_{11}, \gamma_{12}, \ldots, \gamma_{1k}\right)$ which is the $\left(k+1\right) \times 1$ vector of parameters of "weights" of the jth hidden unit and $\gamma_{ji} > 0$ for at least one $i, j = 1, \ldots, k$.

The ARNN model in (9) can easily be written in the form of an ADF regression such that:

$$\left(1-L\right)y_t = \alpha + \rho y_{t-1} + \sum_{k=1}^{p} \delta_k \left(1-L\right) y_{t-k} + \sum_{j=1}^{q} \theta_j F\left(\gamma_j' w_t\right) + \varepsilon_t , \tag{12}$$

where δ_k, $k = 1,...,p$ are parameters in the augmentation component $\left(1-L\right) y_{t-k}$ which controls the whitening of the residuals, ε_t in the test regression.[3] The null and alternative hypotheses for the test are tested in a similar manner to the ADF unit root test in (1).

To be specific, by using the case of an AR(1) process instead of an AR(p) process $\phi_i' w_t$ the ARNN-ADF regression model in (12) becomes,

$$\left(1-L\right)y_t = \alpha + \rho y_{t-1} + \left\{ \frac{\theta}{1+\exp\left[-\left(\gamma_{11} y_{t-1} - c_1\right)\right]} \right\} + \delta_1 \left(1-L\right) y_{t-1} + \varepsilon_t . \tag{13}$$

2.4 Approximating the Hidden Units

Similarly to the STAR nonlinearity (see Granger and Teräsvirta, 1993; Teräsvirta, 1994), the hidden units are approximated using the third-order Taylor series expansion on the logistic STAR function as,

$$F(\gamma_j^T w_t) = F(\gamma_j^T w_t^0) + \frac{\delta(\gamma_j^T w_t^0)}{\delta w_t^T}(w_t - w_t^0)_{|w_t = w_t^0} + \frac{\delta(w_t - w_t^0)}{\delta w_t^T} \frac{\delta^2(\gamma_j^T w_t^0)}{\delta w_t^T \delta w_t^T}(w_t - w_t^0)_{|w_t = w_t^0}$$

$$+ ... + R_h\left(\gamma_j, w_t, w_t^0\right) \tag{14}$$

where $R_h\left(\gamma_j, w_t, w_t^0\right)$ is the remainder of the h[th] order expansion in the Taylors series (Rech, 2002). Then, further simplification of (14) by merging terms of the same orders gives,

$$F(\gamma_j^T w_t) = \lambda_0 + \sum_{t=1}^{q} \lambda_i w_{ti} + \sum_{i=0}^{q} \sum_{j=1}^{q} \lambda_{ij} w_{ti} w_{tj} + \sum_{i=0}^{q} \sum_{j=i}^{q} \sum_{l=j}^{q} \lambda_{ijl} w_{ti} w_{tj} w_{tl} + R_h\left(\gamma_j, w_t, w_t^0\right) \tag{15}$$

and by expanding (15) into a Taylor series around the point γ_{j0} gives:

$$F(\gamma_j^T w_t) = k_0 + \sum_{t=1}^{q} k_i w_{ti} + \sum_{i=0}^{q} \sum_{j=1}^{q} k_{ij} w_{ti} w_{tj} + \sum_{i=0}^{q} \sum_{j=i}^{q} \sum_{l=j}^{q} k_{ijl} w_{ti} w_{tj} w_{tl} + R_h\left(\gamma_j, w_t, 0\right) \tag{16}$$

[3] We can easily re-write (12) to include a linear trend and an intercept.

Then, using (16) in the ARNN-ADF regression in (12) gives,

$$\left(1-L\right)y_t=\alpha+\rho y_{t-1}+\sum_{i=0}^{q}\sum_{j=1}^{q}\kappa_{ij}w_{ti}w_{tj}+\sum_{i=0}^{q}\sum_{j=i}^{q}\sum_{l=j}^{q}\kappa_{ijl}w_{ti}w_{tj}w_{tl}+\sum_{k=1}^{p}\delta_k\left(1-L\right)y_{t-k}+\varepsilon_t \qquad (17)$$

where $\sum_{i=1}^{p}\kappa_i w_{ti}$ is expanded with the linear AR part and augmentation component, $k = p + q$, k is total number of lag, p is the order of autoregressive model, q is the order of hidden unit, p is set to 1 and q is set to 1, $\tilde{\varepsilon}_t$ forms the remainder of the Taylor series expansion, and $w_t=\left(1,y_{t-1}\right)'$ in the case of AR(1) process. Accepting the joint null hypothesis $H_0:\kappa_{ij}=\kappa_{ijl}=0$ implies linearity of the time series, while non-zero of any of κ_{ij} or κ_{ijl} implies nonlinearity of the time series, hence the rejection of the null hypothesis.

3. Empirical Application

The findings from the first generation of unit root tests, namely the ADF test, the PP test, and the DF-GLS test, are reported in Table 1 and Figure 1. The ADF regression model is plotted in Figure 1 where stationarity in the series is mimicked using a straight line trending downward in the case of France, Italy, Netherland and the United Kingdom, while in the case of Sweden, this trends upward. The findings from the ADF unit root test, therefore, indicate that the null hypothesis of unemployment hysteresis could not be rejected for four European countries, while this is rejected in the case of the Netherlands. The findings from the PP test confirm that there is hysteresis of unemployment in all the five European countries, that is the PP test indicating that there is unemployment hysteresis also in Netherlands. The findings from the DF-GLS test show that there is unemployment hysteresis in three European countries, namely France, Italy and Sweden. However, the DF-GLS test indicates that there is no unemployment hysteresis in the Netherlands and the United Kingdom. Despite minor discrepancies in the findings, the empirical findings from the first generation unit root tests seem to demonstrate the presence of the unemployment hysteresis in various European labour markets.

INSERT TABLE 1 ABOUT HERE

The findings from the second generation of unit root tests (i.e. the FADF test) are reported in Table 2 and Figure 2 and the findings from another second generation of unit root tests (i.e. the ADF-SB test) are also reported in Table 2 and Figure 3. As it is observed in Figure 2, the circular movement of the series is mimicked using nonlinear Fourier functions in the FADF regression model, while the ADF-SB regression approximates the dynamics of the series using break lines as shown in Figure 3. The empirical findings from the FADF unit root test confirm the findings from the ADF test that there is unemployment hysteresis in Italy, Sweden and the United Kingdom and no unemployment hysteresis in France and the Netherlands. On the other hand, the ADF-SB unit root test indicates that there is no unemployment hysteresis in the five European countries examined when the estimation model could incorporate a structural break in the time-series of unemployment.

INSERT TABLE 2 ABOUT HERE

Despite some major differences in their findings, the second generation unit root tests seem to indicate that there is no unemployment hysteresis in France and the Netherlands, while they are unable to offer conclusive findings on the unemployment hysteresis in Italy, Sweden and United Kingdom.

The findings from the fractional integration analysis are reported across Tables 3 and 4. In Table 3 we consider a linear set-up of the form:

$$y_t \;=\; \alpha + \beta t \;+\; x_t\,, \qquad (1-L)^d x_t \;=\; u_t, \qquad t \;=\; 1,\, 2,\, \ldots, \tag{18}$$

considering the three standard cases of i) no deterministic terms (α = β = 0 in (18), ii) with an intercept only (β = 0) and iii) with an intercept and a linear time trend. In the results in Table 3, the time trend is not significant in the series and the intercept is significant; thus results for the model with only an intercept are preferred. The estimated values of d are higher than 1 in all cases, ranging from 1.17 (France) to 1.86 (Netherlands). Looking at the confidence intervals, we observe that the I(1) hypothesis cannot be rejected in the case of France, being rejected this hypothesis in favour of d > 1 in all the remaining cases. Thus, according to this model, the hypothesis of persistence is supported in all cases examined of European unemployment.

INSERT TABLE 3 ABOUT HERE

Next, we look at the possibility of non-linear trends using for this purpose the Chebyshev's polynomials in time, i.e,

$$y_t \;=\; \sum_{i=0}^{m} \theta_i \, P_{iT}(t) \;+\; x_t \, ; \qquad (1 - L)^d x_t \;=\; u_t , \qquad t \;=\; 1, 2, \ldots , \tag{19}$$

with m indicating the order of the Chebyshev polynomial $P_{i,T}(t)$ defined as:

$$P_{0,T}(t) \;=\; 1,$$

$$P_{i,T}(t) \;=\; \sqrt{2} \cos\left(i \pi (t - 0.5)/T\right), \qquad t \;=\; 1, 2, \ldots, T; \quad i \;=\; 1, 2, \ldots \tag{20}$$

If $m = 0$ in (19), the model contains an intercept, if $m = 1$ it also includes a linear trend, and if $m > 1$ it becomes non-linear - the higher m is the less linear the approximated deterministic component becomes. The results are presented in Table 4.

INSERT TABLE 4 ABOUT HERE

We observe little evidence of nonlinearities. Only for France and Italy, the θ_3-coefficient is found to be statistically significant. However, for the Netherlands, Sweden and the UK, the two nonlinear coefficients are insignificant. The estimated values of d now range between 1.01 (France) and 1.71 (Netherlands), and the I(1) hypothesis cannot be rejected in the cases of France (1.01), Italy (1.35) and Sweden (1.40), being rejected in favour of d > 1 for UK (1.51) and Netherlands (1.71). Therefore, once more we obtain evidence in favour of hysteresis for all the series examined.

Noting that the fractional integration methods described earlier are part of the second generation unit root tests. The results obtained are able to indicate unemployment hysteresis in those five European countries. Meanwhile, the findings from the third generation of unit root tests, namely the FADF-SB test, are reported in Table 5, Figure 4 and Table 6, Figure 5. In Figure 4, there is quite an obvious improvement using the FADF-SB regression model compared to the plots of FADF in Figure 2. In Table 5, the empirical findings from the FADF-SB unit root test confirm the findings from the ADF-SB test that there is no unemployment hysteresis in the European countries examined. However, some findings from the FADF-SB test contradict with the findings from the FADF test. In Italy, Sweden and the United Kingdom, the FADF test fails to reject the null hypothesis of unemployment hysteresis. But the FADF-SB test could reject the null hypothesis for these three European countries.

INSERT TABLE 5 ABOUT HERE

The findings from the Fourier fractional integration analysis are reported in Table 6. We observe that for France and the U.K. the I(1) hypothesis cannot be rejected but this is strictly above 1 in the remaining three cases though the nonlinear coefficients are all statistically insignificant. These results, indicating unemployment hysteresis in those countries.

INSERT TABLE 6 ABOUT HERE

Finally, findings from the ARNN-ADF test are reported in Table 6 and Figure 5. We see that ARNN-ADF regression mimicked the time series favourably better than FADF-SB and other unit root regression models. This further confirms the ability of the ARNN in approximating time series better than any other linear and nonlinear model specifications. By looking at the ARNN-ADF unit root test results, the bootstrapped critical values are obtained from the Bootstrapped re-sampling method with 10,000 replications. The empirical findings confirmed the findings from the PP test (Table 1) and fractional integration tests (Tables 3, 4 and 6) that there is unemployment hysteresis in all European countries. However, some findings from the ARNN-ADF test and fractional integration tests contradict with the findings from the ADF test and the DF-GLS test. In the case of the Netherlands, the ADF test and the

DF-GLS tests reject the null hypothesis of unemployment hysteresis. However, the ARNN-ADF test and fractional integration tests cannot reject this null hypothesis. Similarly, in the case of the United Kingdom, the DF-GLS test reject the null hypothesis and the ARNN-ADF test and fractional integration tests fail to reject it.

INSERT TABLE 7 ABOUT HERE

Overall, despite some minor differences in their findings, all the unit root analysis offer some consistent findings. The findings indicate that there is unemployment hysteresis in most of the countries examined. However, the unit root analysis detected hysteresis of unemployment in only four of the countries, namely France, Italy, Sweden and the United Kingdom.

4. Conclusions

A new nonlinear unit root test using the neural network is introduced in this paper. The nonlinearity induced by the testing regression model is found to capture well the dynamics of the differenced series, thus this motivated the application of the model in the unit root literature. The unit root test is applied to five European unemployment rates such as France, Italy, Netherland, Sweden and the United Kingdom. A battery of unit root and fractional alternative tests in linear and nonlinear trend specifications were conducted with the ARNN-ADF unit root test. The classical ADF and PP test gave consistent results, only that the hysteresis hypothesis was rejected in the case of the PP test. The ADF-SB and Fourier ADF tests (with or without break date) gave mixed decisions on hysteresis in those countries, while fractional integration test strongly accepted the hypothesis of hysteresis in the five countries. The results of our new test also confirm the presence of hysteresis in those five countries. Findings in this paper support Furuoka (2017) who found unemployment hysteresis in France and Italy using data samples: 1962-2015 and 1991-2015.

In order to further explore the hysteresis of unemployment in these European countries, panel unit root tests using Seemingly Unrelated Regression (SUR) system with Fourier form and neural network nonlinearities are recommended. The SUR system allows for dependence in the time series, which further leads to obtaining consistent estimates, as noted in Breuer et al. (2002). Though, the new test, ARNN-ADF is robust to small sample size since augmentation lag was set to unity, and similar to other tests applied in this paper, other curious researchers could still apply our approach to longer time series. Apart from unemployment hysteresis, researchers could consider the convergence of income, life expectancy, among other time series that are short and annually recorded. Finally, researchers in psychology, computer science, engineering, linguistics, and medicine will find this alternative unit root test useful and more liable when the underlying time series process is a neural network.

References

Adya, M. & Calopy, F. (1998). How effective are neural networks at forecasting and prediction? A review and evaluation, Journal of Forecasting, 17, 481–95.

Balkin, S. D. & Ord, J. K. (2000). Automatic neural network modelling for univariate time series, International Journal of Forecasting, 16, 509–15.

Beran, J. (1995). Maximum likelihood estimation of the differencing parameter for invertible short and long memory ARIMA models, Journal of the Royal Statistical Society, Series B, 57, 659-672.

Binner, J. M., Bissoondeeal, R. K., Elger, T., Gazely, A. M. & Mullineux, A. W. (2005). A comparison of linear forecasting models and neural networks: an application to Euro inflation and Euro Divisia, Applied Economics, 37:6, 665–680, DOI: 10.1080/0003684052000343679.

Breuer, J. B., McNown, R. and Wallace, M. (2002). Series-Specific Unit Root Tests with Panel Data. Oxford Bulletin of Economics and Statistics 64 (5): 527–546.

Burges A. N. & Refenes A. N. (1999). Modelling non-linear moving average processes using neural networks with error feedback: an application to implied volatility forecasting. Signal Process; 74(1), 89–99.

Camarero, M., & Tamarit, C. (2004). Hysteresis vs. natural rate of unemployment: New evidence for OECD countries. Economics Letters, 84, 413– 417.

Camarero, M., Carrión-i-Silvestre, J. L., & Tamarit, C. (2006). Testing for hysteresis in unemployment in OECD countries. New evidence using stationarity panel tests with breaks. Oxford Bulletin of Economics and Statistics, 68, 167–182.

Caner, M. & Hansen, B. E. (2001). Threshold autoregression with a unit root. Econometrica, 69, 1555–1596.

Choi, I. (2002). Combination Unit Root Tests for Cross-Sectionally Correlated Panels. Mimeo, Hong Kong University of Science and Technology. Cambridge University Press. UK.

Choi, I. (2015). Almost all about Unit roots: Foundations, Developments and Applications.

Connor, J. T. & Martin, R. D. (1994). Recurrent neural networks and robust time series prediction. IEEE Transactions on Neural Network; 5(2):240–253.

De Gooijer, J. G. & Hyndman, R. J. (2006). 25 years of time series forecasting. Int. J. Forecast; 22(3): 443–473.

Dickey, D. A & Fuller, W. A. (1979). Distributions of the Estimators for Autoregressive Time Series with a Unit Root, Journal of American Statistical Association, 74(366), 427–481.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica: Journal of the Econometric Society, 49(4), 1057–1072.

Enders, W. & Lee, J. (2012). A unit root test using a Fourier series to approximate smooth breaks. Oxford Bulleting of Economics and Statistics, 74, 574–599.

Engle, R. F. (2003). Risk and volatility: Econometric models and financial practice. 44 West Fourth Street, New York, NY 10012-1126, USA: New York University, Department of Finance (SalomonCentre).

Elliott, G., Rothenberg, T.J. & Stock, J.H. (1996). Efficient Tests for an Autoregressive Unit Root. Econometrica, 64(4), 813–836.

European Commission (2019). Eurostat. https://ec.europa.eu/eurostat/data/database [accessed on 16 March 2019].

Franchi, M. & Ordonez, J. (2008). Common smooth transition trend-stationarity in European unemployment. Economics Letters, 101, 106–109.

Franses, P. H. & van Dijk, D. (2003). Nonlinear Time Series Models in Empirical Finance, Cambridge: Cambridge University Press.

Furuoka, F. (2017). A new approach to testing unemployment hysteresis. Empirical Economics, 53(3), 1253–1280.

Gil-Alana, L. A. & Yaya, O. S. (2018). Testing Fractional Unit Roots with Non-linear Smooth Break Approximations using Fourier functions. MPRA Paper No. 90516.

Gorr, W. L., Nagin, D. & Szcypula, J. (1994). Comparative study of artificial neural network and statistical models for predicting student grade point averages, International Journal of Forecasting, 10, 17–34.

Granger, C. W. J. & Teräsvirta, T. (1993). Modelling Nonlinear Economic Relationships. Oxford: Oxford University Press. Chinese edition 2006: Shanghai University of Finance and Economics Press.

Haggan, V. & Ozaki, T. (1981). Modeling nonlinear vibrations using an amplitude dependent autoregressive time series model, Biometrika, 68, 189-196.

Hornik, K., Stinchcombe, M. & White, H. (1989). Multi-Layer Feedforward Networks are Universal Approximators. Neural Networks, 2, 359–366.

Iacus, S. M. (2011). Statistical data analysis of financial time series and option pricing in R. Chicago: R/Finance, USA.

Im, K. S., Pesaran, M. H. & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115, 53–74.

Johnes, G. (2000). Up around the bend: linear and nonlinear models of the UK economy compared, International Review of Applied Economics, 14, 485–493.

Kapetanios, G., Shin, Y. & Snell, A. (2003). Testing for a Unit Root in the Nonlinear STAR Framework. Journal of Econometrics 112: 359–379.

Lee, J., & Strazicich, M. (2013). Minimum LM unit root test with two structural break. Economics Bulletin, 33, 2483–2492.

Levin, A., Lin, C. & Chu, C. J. (2002). Unit Root Tests in Panel Data: Asymptotic and Finite-sample Properties, Journal of Econometrics, 108, 1–24.

Maddala, G. S. & Wu, S. (1999). A Comparative Study of Unit Root Tests with Panel Data and a new simple test. Oxford Bulletin of Economics and Statistics, 61, 631–652.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics, 11, 601–618.

Moon, H. R. & Perron, P. (2004), Testing for Unit Root in Panels with Dynamic Factors. Journal of Econometrics, 122, 81–126.

Moshiri, S. and Cameron, N. (2000). Neural Network versus Econometric Models in Forecasting Inflation. Journal of Forecasting 19, 201–217.

Nag, A. K. & Mitra, A. (2002) Forecasting daily foreign exchange rates using genetically optimized neural networks, Journal of Forecasting, 21, 501–511.

Escribano, A. and Jorda, O. (1999). Improved testing and specification of smooth transition regression models. In: Rothman P. (eds) Nonlinear Time Series Analysis of Economic and Financial Data. Dynamic Modeling and Econometrics in Economics and Finance, vol 1. Springer, Boston, MA

Perron, P. (2006). Dealing with structural breaks. Palgrave Handbook of Econometrics, 1, 278–352.

Perron, P. & Vogelsang, T. J. (1992). Non-stationarity and level shifts with an application to purchasing power parity. Journal of Business, Economics and Statistics, 10(3), 301–320.

Pesaran, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross Section Dependence. Journal of Applied Econometrics, 22, 265–312.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335–346.

Rech, G. (2002). Modelling and Forecasting Economic Time Series with Single Hidden-Layer Feed forward Autoregressive Artificial Neural Networks. PhD Thesis. Stockholm School of Economics.

Robinson, P. M. (1994). Efficient tests of nonstationary hypotheses. Journal of American Statistical Association. 89, 1420–1437

Robinson P. M. (2005). Modelling memory of economic and financial time series. London School of Economics and Political Science.

Salisu, A. A., Ogbonna, A. E. and Omosebi, P. A. (2018). Does the choice of estimator matter for forecasting? A revisit. Working Papers 053, Centre for Econometric and Allied Research, University of Ibadan.

Shin, D. & Lee, O. (2001). Tests for asymmetry in possibly nonstationary time series data, Journal of Business and Economic Statistics 19, 233−244.

Sowell, F. (1992). Maximum likelihood estimation of stationary univariate fractionally integrated time series models, Journal of Econometrics 53, 165.18

Stanca, L. (1999). Asymmetries and nonlinearities in Italian macroeconomic fluctuations, Applied Economics, 31, 483–499.

Taylor, A. M. (2002). A century of purchasing power parity. Review of Economics and Statistics. 84, 139–150.

Taylor, M. P. & Sarno, L. (1998). The Behavior of Real Exchange Rates during the Post-Bretton Woods Period. Journal of International Economics, 46, 281–312.

Tealab, T., Hefny, H. and Badr, A. (2017). Forecasting of nonlinear time series using ANN, Future Computing and Informatics Journal, 2(1), 39–47.

Teräsvirta, T. (1994). Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models. Journal of the American Statistical Association, 89, 208–218.

Teräsvirta, T. (2005). Forecasting economic variables with nonlinear models. SSE/EFI working paper in economics and finance. Stockholm: Department of Economic Statistics; p. 598.

Tiao, G. C. and Tsay, R. S. (1994). Some advances in non-linear and adaptive modelling in time-series, Journal of Forecasting, 13, 109–131.

Tong, H. (1990). Nonlinear Time Series: A Dynamical System Approach. Oxford University Press, Oxford, UK.

van Dijk, D., Franses, P. H., and Paap, R. (2002). A nonlinear long memory model, with an application to US unemployment. Journal of Econometrics, 110, 135–165.

van Dijk, D., Medeiros, M. C. and Teräsvirta, T. (2004). Linear models, smooth transition autoregressions, and neural networks for forecasting macroeconomic time series: a re-examination. Department of Economics PUC-Rio, Pontifical Catholic University of Rio de Janeiro Rua Marques de Sao Vicente 225-Rio de Janeiro 22453-900, RJ.

Yaya, O. S., Ogbonna, A. E. and Atoi, N. V. (2019). Are Inflation Rates in OECD countries actually Stationary during 2011-2018? Evidence based on Fourier Nonlinear Unit Root tests with breaks. MPRA paper 93937, University Library of Munich, Germany.

Yaya, O. S., Ogbonna, A. E. and Mudida, R. (2019). Hysteresis of Unemployment rate in Africa: New Findings from Fourier ADF test. Quality and Quantity International Journal of Methodology. https://doi.org/10.1007/s11135-019-00894-6.

Zivot, E. and Andrews, D. W. K. (1992). Further evidence on Great Crash, the oil price shock and the unit root hypothesis. Journal of Business, Economics and Statistics, 10, 251–270.

Table 1: Findings from the first generation unit root analysis

Countries	ADF test	PP test	DF-GLS test
France	-2.927	-2.492	-2.934
Italy	-2.712	-1.722	-2.703
Netherlands	-4.363**	-2.292	-4.111**
Sweden	-2.778	-1.679	-2.936
United Kingdom	-3.277	-1.938	-3.270*

Notes: The five percent critical value for the ADF test and the PP test is -3.548 and their one percent critical value is -4.252 (MacKinnon, 1996). The lag lengths in the empirical analysis are fixed to one due to this limited number of observations. The five percent critical values for the DF-GLS are -3.190 and its one percent critical value is -3.770 (Elliott *et al.*, 1996). * indicates significance at the five percent level, ** indicates significance at the one percent level.

Table 2
Findings from second generation unit root analysis I (FADF test and ADF–SB test)

Countries	FADF test	Frequency	ADF–SB test	Structural break
France	-4.818*	2	-4.639**	1999 (0.47)
Italy	-3.614	2	-4.166*	2010 (0.80)
Netherlands	-5.163**	1	-5.942**	2011 (0.80)
Sweden	-3.590	1	-5.524**	1991 (0.20)
United Kingdom	-3.529	2	-5.575**	2008 (0.72)

Notes: Numbers in parentheses indicate the break-position (λ); * indicates significance at the 5% level, ** indicates significance at the 1% level; critical values were obtained from Table 3 (Furuoka, 2017).

Table 3
Findings from second generation unit root analysis (Estimates of d in a linear set-up)

Countries	Country	No terms	An intercept	A linear time trend
France	FRANCE	0.98 (0.74, 1.37)	**1.17** **(0.71, 1.81)**	1.17 (0.74, 1.83)
Italy	ITALY	1.03 (0.83, 1.34)	**1.03** **(1.20, 2.04)**	1.56 (1.21, 2.07)
Netherlands	NETHERLANDS	0.77 (0.60, 1.20)	**0.77** **(1.33, 2.47)**	1.84 (1.29, 2.49)
Sweden	SWEDEN	1.16 (0.79, 1.70)	**1.16** **(1.09, 2.14)**	1.50 (1.09, 2.14)
United Kingdom	U.K.	0.93 (0.66, 1.33)	**1.57** **(1.10, 2.19)**	1.57 (1.09, 2.19)

In bold the significant cases with respect to the deterministic terms.

Table 4
Findings from second generation unit root analysis (Estimates of d in a non-linear setting)

Countries	Series	*d*	θ_0	θ_1	θ_2	θ_3
France	FRANCE	1.01 (0.33, 1.77)	**8.538** **(4.40)**	-0.257 (-0.22)	- 0.033	**-0.595** **(1.79)**
Italy	ITALY	1.35 (0.85, 1.91)	**10.606** **(2.05)**	-1.451 (-0.44)	0.593 (0.52)	**-1.483** **(-2.25)**
Netherlands	NETHERLANDS	1.71 (1.25, 2.46)	**16.732** **(1.65)**	-6.099 (0.73)	1.989 (0.87)	-0.880 (0.77)
Sweden	SWEDEN	1.40 (0.95, 2.10)	**11.764** **(1.80)**	-3.498 (-0.60)	- 0.971	-1.044 (-0.95)
United Kingdom	U.K.	1.51 (1.96, 2.18)	**9.606** **(1.97)**	-0.396 (-0.06)	0.012 (0.70)	-0.048 (-0.04)

In parenthesis in the second column, the 95% confidence interval for d. In the third to the sixth column are t-values for parameters θ_0, θ_1, θ_2 and θ_3, respectively. In bold indicates significance of estimates at 5% level.

Table 5
Findings from third generation unit root analysis (FADF-SB test)

Countries	FADF-SB test	Frequency	Structural break
France	-5.397**	2	1999 (0.47)
Italy	-6.826**	2	2011 (0.80)
Netherlands	-6.022**	2	2011 (0.80)
Sweden	-5.867**	2	1992 (0.22)
United Kingdom	-6.985**	2	1987 (0.13)

Notes: Numbers in parentheses indicate the break-position (λ); * indicates significance at the 5% level, ** indicates significance at the 1% level; critical values were obtained from Table 3 (Furuoka, 2017).

Table 6
Findings from second generation unit root analysis (Fourier Fractional integration analysis)

Countries	Series	*d*	α	β	λ_1	γ_1
France	FRANCE	1.14 (0.57, 1.80)	**7.013** **(5.85)**	0.057 (0.37)	0.693 (0.69)	-0.002 (-0.002)
Italy	ITALY	1.52 (1.09, 2.02)	**5.835** **(2.38)**	0.146 (0.28)	1.492 (0.75)	1.107 (0.48)
Netherlands	NETHERLANDS	1.79 (1.15, 2.48)	**7.065** **(1.78)**	-0.030 (-0.03)	- 0.960	2.641 (0.69)
Sweden	SWEDEN	1.48 (1.02, 2.15)	**5.566** **(1.82)**	-0.066 (-0.09)	- 0.959	-1.556 (-0.48)
United Kingdom	UNITED KINGDOM	1.51 (0.97, 1.217)	**9.108** **(3.35)**	-0.058 (-0.10)	- 0.383	1.719 (0.67)

Notes: * indicates significance at the 5% level, ** indicates significance at the 1% level.

Table 7
Findings from the ARNN-ADF test

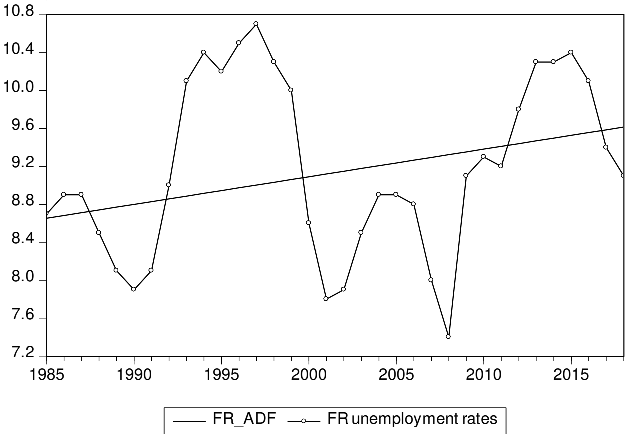
Countries	ARNN-ADF statistics	Bootstrapped 5% critical value	Bootstrapped 1% critical value
France	-1.424	-2.821	-3.910
Italy	-0.646	-3.126	-4.219
Netherlands	-0.513	-2.955	-3.931
Sweden	-0.848	-2.946	-3.808
United Kingdom	0.389	-3.081	-4.084

Notes: * indicates significance at the 5% level, ** indicates significance at the 1% level.

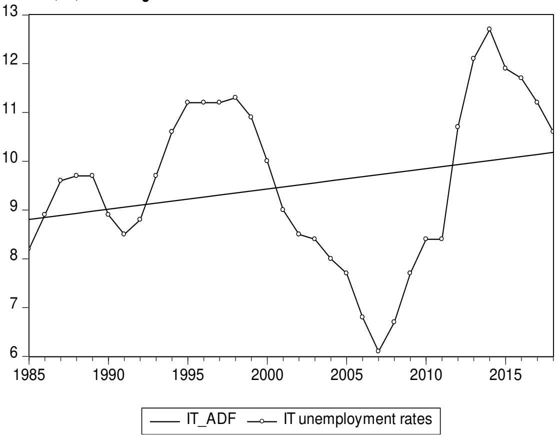
Appendix: Graphs

Figure 1: ADF test

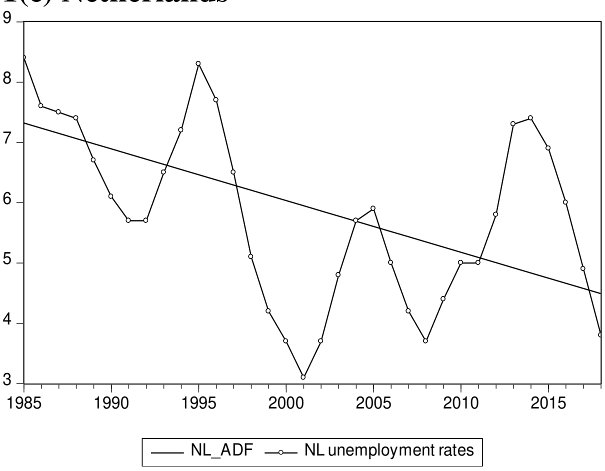
1(a) France



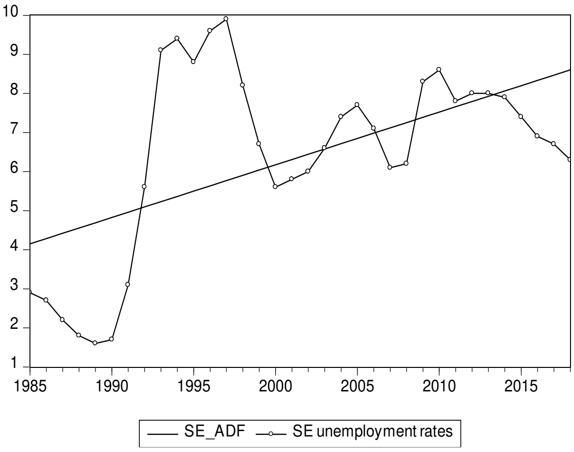
1(b) Italy



1(c) Netherlands



1(d) Sweden



1(e) United Kingdom

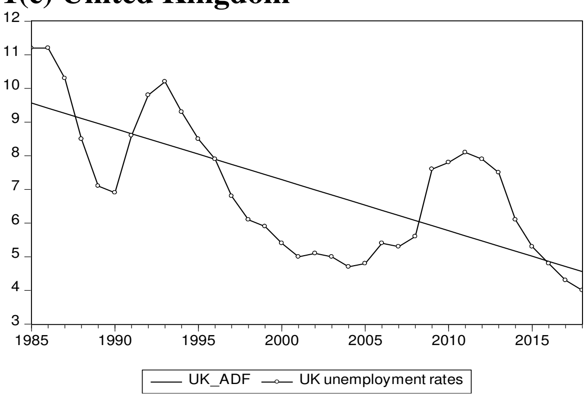
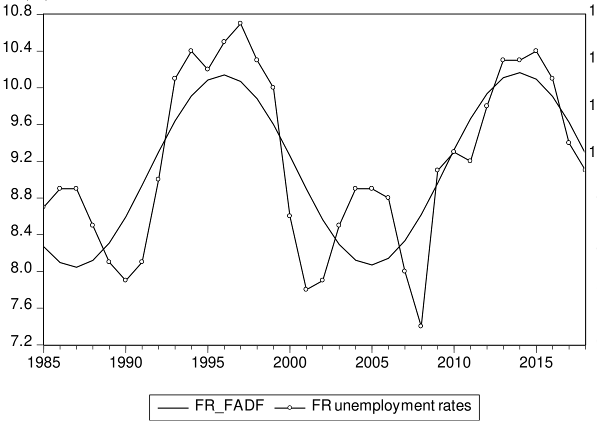
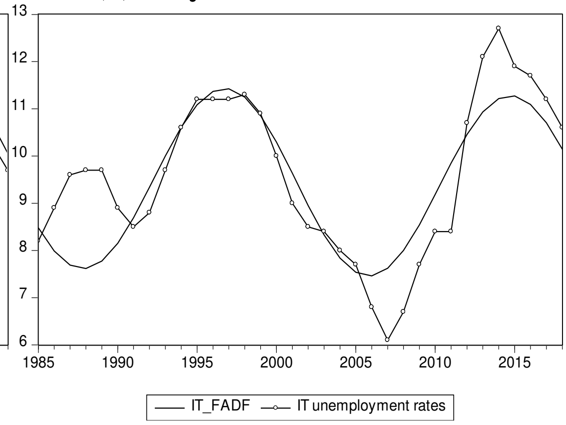


Figure 2: FADF test

2(a) France



2(b) Italy



2(c) Netherlands

2(d) Sweden

2(e) United Kingdom

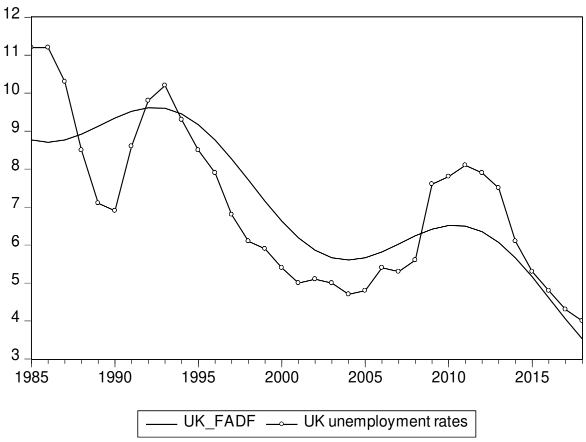
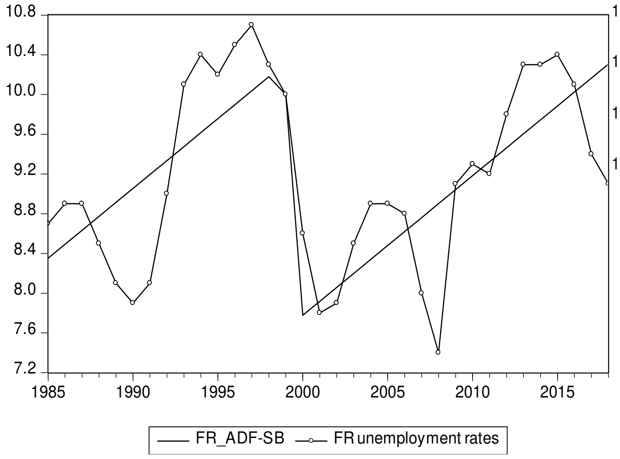
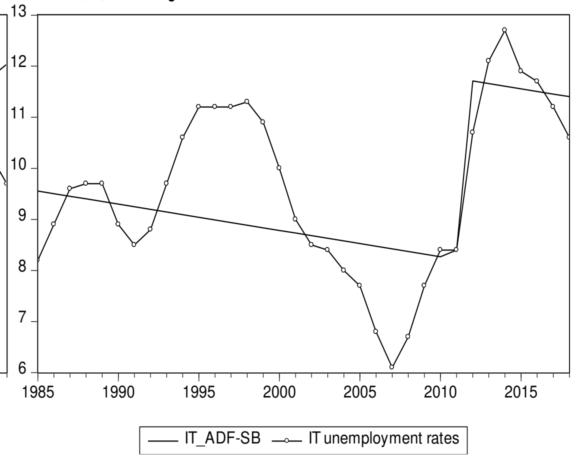


Figure 3: ADF-SB test

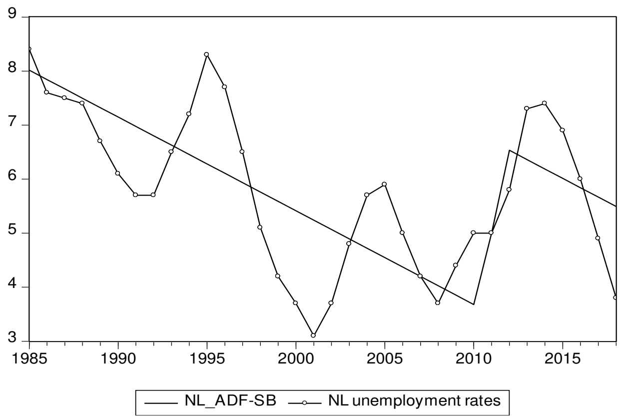
3(a) France



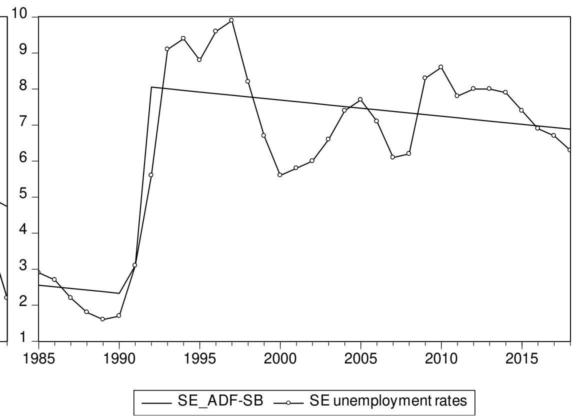
3(b) Italy



3(c) Netherlands



3(d) Sweden



3(e) United Kingdom

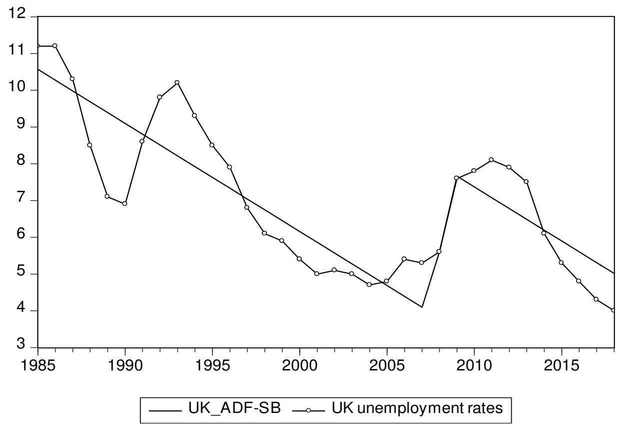
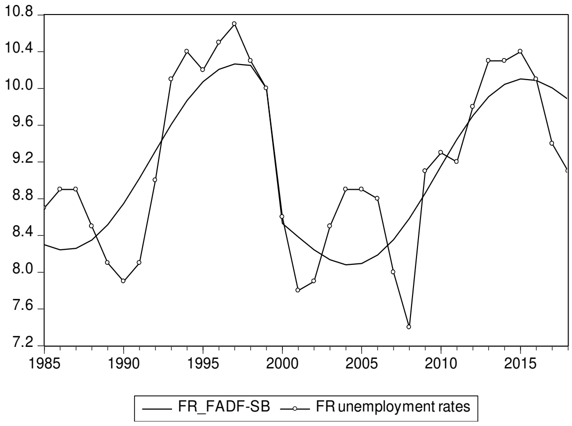
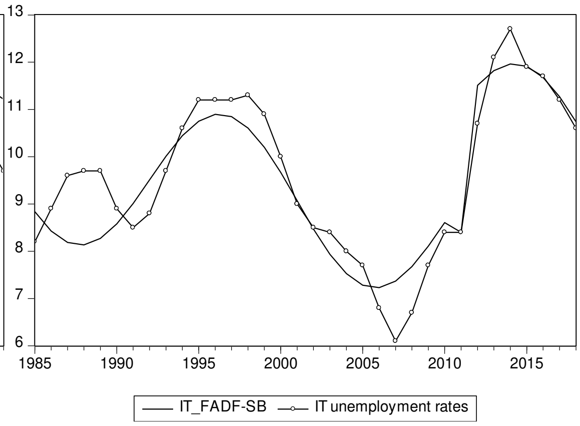


Figure 4: FADF-SB test

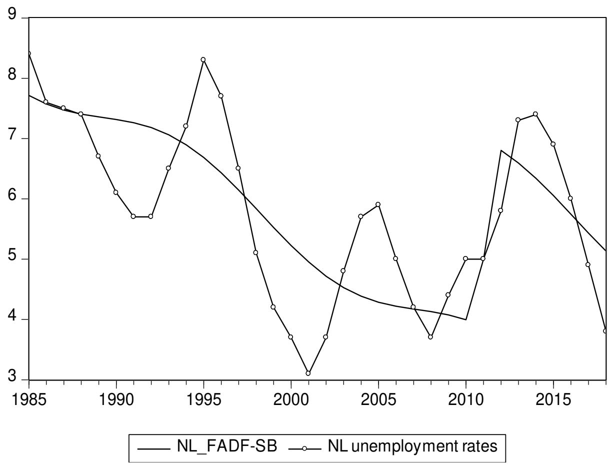
4(a) France



4(b) Italy



4(c) Netherlands



4(d) Sweden

4(e) United Kingdom

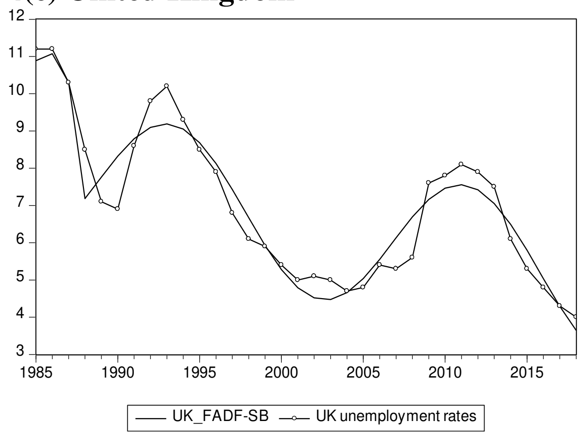
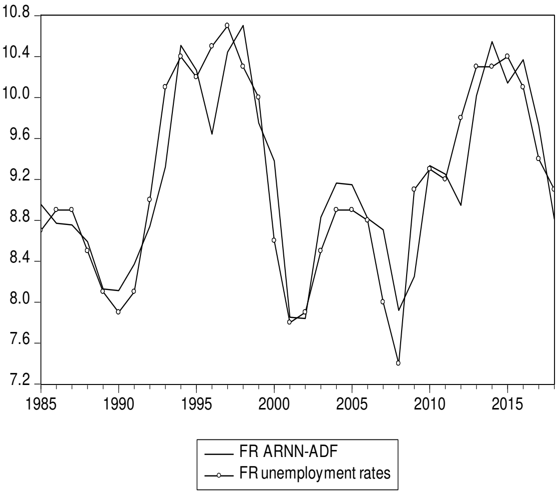
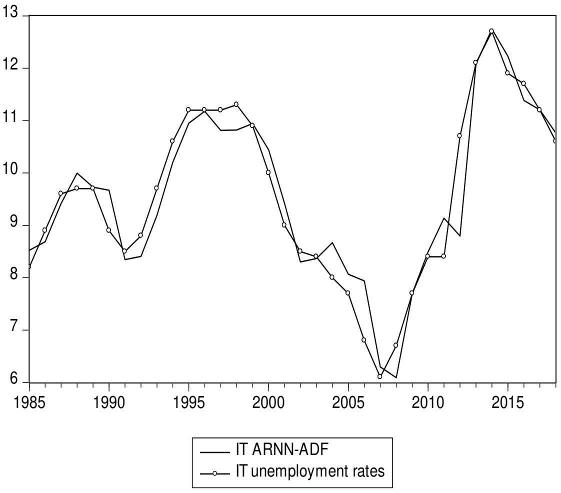


Figure 5: ARNN-ADF test

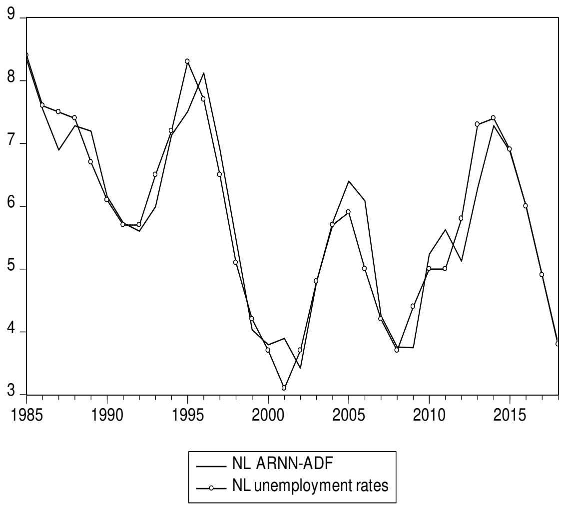
5(a) France



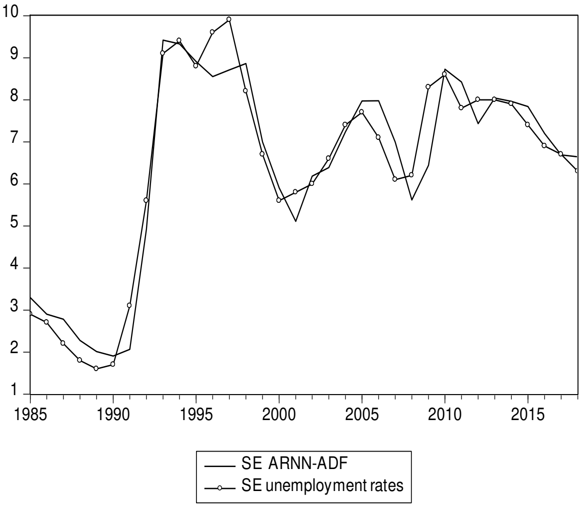
5(b) Italy



5(c) Netherlands



5(d) Sweden



5(e) United Kingdom