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TESTING UNEMPLOYMENT THEORIES: A MULTIVARIATE LONG MEMORY APPROACH

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This paper investigates the empirical relevance of both the hysteresis and the natural rate hypothesis on unemployment in three major economies, namely the UK, the US and Japan, by estimating the degree of dependence in the unemployment series. Both univariate and multivariate long memory methods are used. The results vary depending on whether the former or the latter approach is followed. Specifically, when taking a univariate approach, the unit root null cannot be rejected in case of the UK and Japanese unemployment series, and some degree of mean reversion ($d < 1$) is found in the case of the US unemployment rate. When applying multivariate methods instead, higher orders of integration are still found for the UK and Japanese series, but the natural rate hypothesis cannot be rejected in the case of the US.

JEL classification codes: C22, C32, E24
Key words: unemployment rate, multivariate long memory, fractional integration

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I. Introduction

This paper investigates the empirical relevance of different unemployment theories in three major economies, namely the UK, the US and Japan, by estimating the degree of dependence in the unemployment series. For this purpose, it applies long memory methods and in particular, fractional integration techniques, which are more general than the standard approaches based on integer degrees of differentiation only considering the cases of stationarity $I(0)$ and nonstationarity $I(1)$. The existing empirical literature has either used univariate fractional integration or multivariate fractional cointegration methods for estimating the differencing parameter with parametric, semi parametric or non-parametric techniques; little attention has instead been paid to multivariate $I(d)$ processes, which allow for potential correlation among the variables of interest. In general, the unemployment rate follows the swings of the business cycle, therefore one would expect that the higher the degree of business cycle synchronization is the more correlated unemployment rates in different countries will be.

The present is a thorough study using both univariate and multivariate techniques. It shows that the results vary substantially depending on whether the former or the latter approach is followed, and that taking into account the correlations between the variables is crucial to estimate the degree of integration of the series accurately and therefore to obtain reliable evidence to discriminate between different unemployment theories.[1]

The structure of the paper is as follows. Section II briefly reviews the main unemployment theories and what they imply for the degree of dependence of the data. Section III outlines the methodology. Section IV describes the data and discusses the empirical results, while Section V concludes the paper.

II. Unemployment theories

There are two main theoretical approaches to understanding the behaviour of the unemployment rate. The natural rate theory (see Friedman 1968 and Phelps 1967,

[1] The natural rate (NAIRU) hypothesis (Phelps 1967 and Friedman 1968) claims that unemployment should converge to a natural rate in the long-run. If this hypothesis is correct, deviations from the natural rate will die in the short run. Blanchard and Summers (1987), however, argue that unemployment exhibits hysteresis, implying that economic shocks have permanent or very persistent effects on unemployment rates.

1968) implies that it should fluctuate around a stationary equilibrium level, known as the natural rate or NAIRU, which is determined by economic fundamentals. In "structuralist" models (see Phelps 1994) this is "endogenised", i.e. the equilibrium level to which unemployment reverts when hit by shocks can shift over time as a result of infrequent structural breaks reflecting changes in economic fundamentals. Hence mean-reversion occurs provided the breaks are taken into account. Various theoretical models have been put forward to endogenise the natural rate of unemployment. They rely alternatively on productivity growth (Pissarides 1990), real interest rates (Blanchard 1999), stock prices (Phelps 1999)), institutional variables (Nickell 1998 and Nickell el al. 2000), or the interaction between institutional and macroeconomic variables (Blanchard and Wolfers 2000).

The observed high persistence of unemployment in Europe led to the development of an alternative class of models, i.e. hysteresis models (see Blanchard and Summers 1986, 1987 and Barro 1988) where unemployment is a path-dependent variable, with temporary shocks having permanent or very highly persistent effects. In this framework, unemployment may exhibit long memory, with a (near) unit root.

Unemployment theories have been tested in a huge number of papers. Initially, standard unit root tests (such as Dickey and Fuller 1979, ADF, or Phillips and Perron 1988, PP) were carried out (see, e.g., Blanchard and Summers 1986, and Alogoskoufis and Manning 1988), often supporting the hysteresis hypothesis (see, e.g., the studies of Gordon 1989 for France, Germany, the US, Japan and the UK, Graafland 1991 for the Netherlands, Lopez et al. 1996 for Spain and Wilkinson 1997 for Canada). Studies allowing for structural breaks (see, e.g., Mitchell 1993, Bianchi and Zoega 1998, and Papell et al. 2000) have tended instead to support structuralist theories. Mixed evidence is also reported in the more recent literature (see, e.g., Amable and Mayhew 2011, Fosten and Ghoshray 2011, Holl and Kunst 2011, King and Morley 2007, Srinivasau and Mitra 2012).

Panel approaches have subsequently been used to deal with the well-known problem of the low power of standard unit root tests (see, e.g., Song and Wu 1998 and Leon-Ledesma 2002), generally finding that hysteresis models work better in Europe, and NAIRU models in the US. Panel analyses allowing for breaks as well (see Murray and Papell 2000 and Strazicich, Tieslau and Lee 2009) are more supportive of structuralist theories.

Another recent strand of the literature estimates fractionally integrated (ARFIMA) models to test for long memory in the unemployment rate (see, for instance, Tschernig and Zimmermann 1992, Crato and Rothman 1996, Gil-Alana 2001, 2002, etc.). By allowing for fractional orders of integration, such a modelling approach is suitable for both stationary processes (NAIRU models), and highly persistent/nonstationary ones (hysteresis hypothesis), and by incorporating structural breaks it can also be used to model processes exhibiting regime change (structuralist theories). This is another important issue since fractional integration could be a spurious phenomenon caused by the presence of breaks that have not been taken into account. Recent studies of this type include Caporale and Gil-Alana (2007, 2008). The former paper proposes a model of the US unemployment as a fractionally integrated process interacting with some non-linear functions of labour-demand variables such as real oil prices and real interest rates, and also finds evidence of a long memory component. The results are consistent with a hysteresis model with path dependence rather than a non-accelerating inflation rate of unemployment (NAIRU) model. The latter paper uses a general procedure for fractional integration and structural breaks at unknown points in time, allowing for different orders of integration and deterministic components in each subsample as well as for non-linearities. This study suggests that a structuralist interpretation is more appropriate for the US and Japan, whilst a hysteresis model accounts better for the UK experience. However, these two papers are based on univariate models that do not take into account the possible correlation between the unemployment series.

III. Methodology

For the purposes of the present study, we define an $I(0)$ process as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. In this context, x_t is said to be $I(d)$ if it can be represented in the form:

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \ldots, \tag{1}$$

with $x_t = 0$ for $t \leq 0$, where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is $I(0)$. The polynomial $(1-L)^d$ in equation (1) can be expressed in terms of its binomial expansion, such that, for all real d,

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d L + \frac{d(d-1)}{2} L^2 - \ldots \tag{2}$$

and thus

$$(1-L)^d x_t = x_t - dx_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \ldots$$

In this context, d plays a crucial role since it indicates the degree of dependence of the time series: the higher the value of d is, the higher the level of association will be between the observations. The above process also admits an infinite Moving Average (MA) representation. Thus, for example, assuming that u_t in (1) is a white noise process, the process can be expressed as

$$x_t = \sum_{k=0}^{\infty} a_k u_{t-k}, \text{ where } a_k = \frac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)},$$

and $\Gamma(x)$ represents the Gamma function. Thus, the impulse responses are also clearly affected by the magnitude of d, and the higher the value of d is, the higher the responses will be.

Given the parameterisation in (1), several cases can be distinguished depending on the value of d. Specifically, if $d = 0$, $x_t = u_t$, x_t is said to be "short memory" or $I(0)$, and if the observations are autocorrelated, they are "weakly autocorrelated" (e.g., autoregressive), in the sense that they decay at an exponential rate; if $d > 0$, x_t is said to be "long memory", or "strongly autocorrelated", because of the strong association between observations far away in time If d belongs to the interval (0, 0.5), x_t is still covariance stationary, while $d \geq 0.5$ implies nonstationarity. Finally, if $d < 1$, the series is mean reverting in the sense that the effects of shocks disappear in the long run, contrary to what happens if $d \geq 1$ when they persist forever.[2]

As mentioned before, estimating d is crucial to be able to discriminate between different unemployment theories. Specifically, $d = 0$ can be thought of as being consistent with the NAIRU hypothesis, while long memory ($d > 0$) and unit roots ($d = 1$) support the "hysteresis" approach to unemployment.

In a univariate context, there exist several methods for estimating and testing the fractional differencing parameter d. Some of them are parametric while others

[2] In the paper we assume that $x_t = u_t = 0$ for $t \leq 0$. In other words, we adopt the Type II definition of fractional integration (see Marinucci and Robinson 1999 for the differences from other processes). This is important since the limit distribution of the procedures employed is clearly affected by the choice of Type I/Type II definitions of fractional integration (Davidson and Hashimzade 2009). Also, in the case of d in the interval [0.5, 1) some authors argue that "mean reversion" is a misnomer given the nonstationarity nature of the process (Phillips and Xiao 1999).

are semi parametric and can be specified in the time or in the frequency domain. In this paper, we use a Whittle estimate of d in the frequency domain (Dahlhaus 1989) along with a testing procedure, which is based on the Lagrange Multiplier (LM) principle and that also uses the Whittle function in the frequency domain. It tests the null hypothesis:

$$H_o: d = d_o, \tag{3}$$

for any real value d_o, in a model given by the equation (1), where x_t can be the errors in a regression model of the form:

$$y_t = \beta^T z_t + x_t, \quad t = 1, 2, ..., \tag{4}$$

where y_t is the observed time series, β is a (k×1) vector of unknown coefficients and z_t is a set of deterministic terms that might include an intercept (i.e., $z_t = 1$), an intercept with a linear time trend ($z_t = (1, t)^T$), or any other type of deterministic processes. Robinson (1994) showed that, under certain very mild regularity conditions, the LM-based statistic ($\hat{r}$):

$$\hat{r} \rightarrow_d N(0,1) \quad as \quad T \rightarrow \infty, \tag{5}$$

where " $\rightarrow_d$" stands for convergence in distribution, and this limit behaviour holds independently of the regressors z_t used in (4) and the specific model for the $I(0)$ disturbances u_t in (1).[3]

As in other standard large-sample testing situations, Wald and LR test statistics against fractional alternatives have the same null and limit theory as the LM test of Robinson (1994). Lobato and Velasco (2007) essentially employed such a Wald testing procedure, even though it requires a consistent estimate of d; therefore the LM test of Robinson (1994) seems computationally more attractive.

[3] A brief description of this procedure can be found in the Appendix.

A semiparametric Whittle approach (Robinson 1995) that only uses frequencies close to zero will also be applied in the paper.

A disadvantage of the univariate methods is that they do not take into account the potential cross-dependence of the series. Thus, in this paper, we also consider multivariate models of the form:

$$\begin{aligned} D(L)x_t &= u_t, \\ [I - F_p(L)]u_t &= \varepsilon_t, \end{aligned} \tag{6}$$

where $D(L)$ is a $(n \times n)$ diagonal matrix with $(1-L)^{d_i}$ on the main diagonal, where d_i indicates the degree of integration of the i^{th} variable, and u_t is now an $(n \times 1)$ vector of $I(0)$ variables that may have a finite Vector Autoregressive (VAR) representation with p lags, ε_t is $(n \times 1)$ vector of i.i.d errors with 0 mean and variance-covariance matrix V.

The spectral density matrix of the process given by (6) is a $(n \times n)$ matrix:

$$f_x(\omega,\theta) = (2\pi)^{-1} D(e^{-i\omega})^{-1} \left[I - F_p(e^{-i\omega})\right]^{-1} V \left[I - F_p(e^{-i\omega})\right]^{-1} D(e^{i\omega})^{-1},$$

where i is a complex number, $\omega = \frac{2\pi j}{T}, j = 0,1,\ldots,\frac{T}{2}-1$ are Fourier frequencies, $D(e^{-i\omega}) = D_0 + D_1 e^{-i\omega} + D_2 e^{-2i\omega} + \ldots.$ is an infinite order matrix polynomial and $D(e^{i\omega})$ is its complex conjugates; matrices $D_m, m = 0,1,\ldots$ are diagonal with coefficients given by the binomial expansion as in (2); $F_p(e^{-i\omega}) = F_1 e^{-i\omega} + \ldots + F_p e^{-pi\omega}$ and $F_p(e^{i\omega})$ are complex conjugates.[4] The vector of parameters of the VARFISMA model θ contains parameters of fractional integration, autoregressive parameters from the polynomial $F_p(L)$, and parameters from the variance-covariance matrix of the vector of errors, V.

To estimate the process given by (6) we use approximate frequency domain maximum likelihood, best known as Whittle estimation, proposed by i.a. Boes et al. (1989). The discussion of the multivariate version of the estimation can be found in Hosoya (1996).

[4] In a narrow sense, the spectral density does not exist for nonstationary processes. Some authors use the term "pseudo spectrum".

An approximate log-likelihood function of θ based on $x_{i,t}, t = 1,...,T$, is given up to constant multiplication, by

$$\ln L(\omega,\theta) = -\sum_{j=0}^{T/2-1}\left[\ln\det f_x(\omega_j,\theta) + tr\, f_x^{-1}(\omega_j,\theta) I_T(\omega_j,x)\right],$$

where $I_T(\omega_j, x)$ is the $(n\times n)$ periodogram matrix. For each j, the elements of the main diagonal of $I_T(\omega_j, x)$ are points of the periodogram of x_i at frequency ω_j, which are real numbers, while the off diagonal elements are points of the cross-periodograma, which are complex and they are complex conjugate of each other (see, e.g., Lovcha and Perez-Laborda 2014 for further details of the estimation method).

IV. Data and empirical results

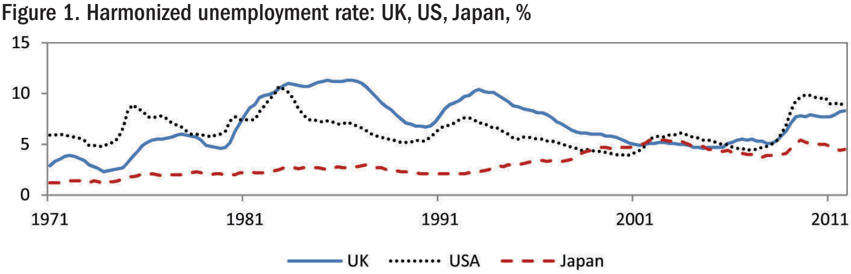
The data source is the St. Louis Federal Reserve Bank database. We use the following three series:

1. Harmonized unemployment rate: All Persons for United Kingdom, quarterly, seasonally adjusted, 1971-01-01 to 2011-10-01, series ID: GBRURHARMQDSMEI.

2. Harmonized unemployment rate: All Persons for the United States, quarterly, seasonally adjusted, 1971-01-01 to 2011-10-01, series ID: USAURHARMQDSMEI.

3. Harmonized unemployment rate: All Persons for Japan, monthly, seasonally adjusted, 1971-01-01 to 2011-10-01, series ID: JPNURHARMMDSMEI, transformed to quarterly by taken average of months inside a quarter.[5]

Figure 1. Harmonized unemployment rate: UK, US, Japan, %



[5] Seasonal adjustments may entail an upward bias in the estimation of the spectral density function. Nevertheless, since the main issue in the paper is to test unemployment theories rather than modelling seasonality we have preferred to use seasonally adjusted data.

Prior to the estimation we take logs of the series, and for the multivariate approach we standardise them by subtracting the mean.

We start with the univariate approach and estimate d in the model given by the equations (1) and (4) with $z_t = (1, t)^T$, $t > 0$, 0 otherwise, i.e.,

$$y_t = \alpha + \beta t + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, ..., \tag{7}$$

where y_t is the log-transformed series, with different assumptions for the $I(0)$ error term u_t. In particular, we assume in turn that u_t is white noise and autocorrelated, in the latter case using a non-parametric specification due to Bloomfield (1973). In this model, u_t is specified exclusively in terms of its spectral density function, which is given by

$$f(\lambda;\tau) = \frac{\sigma^2}{2\pi} \exp\left(2\sum_{r=1}^{m} \tau_r \cos(\lambda r)\right) \tag{8}$$

where σ^2 is the variance of the error term, and m is the number of parameters required to describe the short run dynamics of the series.[6] Its main advantage is that it mimics the behaviour of ARMA (Auto Regressive Moving Average) structures with a small number of parameters. Moreover, it works extremely well in the context of the LM tests of Robinson (1994) (Gil-Alana 2004).

Given the above model, we consider the three standard cases examined in the literature, i.e., the case of no regressors, i.e. $\alpha = \beta = 0$ in (7), an intercept (α unknown and $\beta = 0$) and an intercept with a linear time trend (α and β unknown in (7)). The t-values (not reported) indicate that a time trend is not required, an intercept being sufficient to describe the deterministic part of the process in all cases.

[6] This model is non-parametric in the sense that the functional form for the unemployment series is not explicitly shown, and their properties are described exclusively through the spectral density function.

Table 1. Estimates of d (and 95% confidence intervals) from the univariate approach

	Parametric Robinson (1994)	Semiparametric Robinson (1995)	Non-parametric Bloomfield (1973)
UNITED KINGDOM	1.457 (1.354, 1.588)	0.954 (0.771, 1.228)	1.081 (0.667, 1.433)
JAPAN	1.126 (1.019, 1.266)	0.894 (0.771, 1.228)	0.862 (0.534, 1.346)
UNITED STATES	1.052 (0.944, 1.299)	0.780 (0.771, 1.228)	0.683 (0.298, 0.993)

Note: The values of d are the Whittle estimates, while the values in parenthesis refer to the 95% confidence intervals of the non-rejections using Robinson's (1994) approach

We report in Table 1 the estimates of d along with the 95% confidence band of the non-rejection values of d using Robinson's (1994) parametric approach. Starting with the case of white noise disturbances, it can be seen that the three estimates of d are above 1 and the unit root null hypothesis is rejected in favour of higher degrees of integration for the UK and Japan but not for the US. However, when using the semi parametric method of Robinson (1995) the three estimates are below 1 and the unit root cannot be rejected for any of the three series. Finally, when using the non-parametric approach of Bloomfield (1973) the unit root null cannot be rejected for the UK and Japan, but it is rejected in favour of mean reversion ($d < 1$) in the US case. The results for the three specifications are consistent in the sense the highest degrees of integration (and thus of dependence) are found for the UK, followed by Japan, with the US exhibiting the lowest degrees of integration.

The multivariate model we consider is the following:

$$\begin{pmatrix} (1-L)^{d_{UK}} & 0 & 0 \\ 0 & (1-L)^{d_{US}} & 0 \\ 0 & 0 & (1-L)^{d_{JP}} \end{pmatrix} \begin{pmatrix} y_{UK,t} \\ y_{US,t} \\ y_{JAP,t} \end{pmatrix} = \begin{pmatrix} u_{UK,t} \\ u_{US,t} \\ u_{JAP,t} \end{pmatrix}, \quad t = 1, 2, \dots ,$$

where y_t is now a (3×1) vector with the unemployment series, and u_t is a VAR process of the form:

$$\left(I - F_p(L)\right)u_t = \varepsilon_t, \qquad t = 1, 2, \dots ,$$

with $F_p(L)$ is a (3×3) matrix of the stationary VAR coefficients, and ε_t as a white noise vector process, with variance covariance matrix

$$V(\varepsilon_t) = \Lambda\Lambda^T, \quad \Lambda = \begin{pmatrix} \omega_{11} & 0 & 0 \\ \omega_{21} & \omega_{22} & 0 \\ \omega_{21} & \omega_{22} & \omega_{23} \end{pmatrix}$$

and $p = 4$ according to the Akaike Information Criterion.

Table 2. Estimated coefficients in the multivariate model

			UNITED KINGDOM			JAPAN			UNITED STATES		
Estimates of d			d_{UK} = 0.615 (0.171)			d_{JAP} = 0.568 (0.307)			d_{US} = 0.086 (0.221)		
F_1			F_2			F_3			F_4		
0.836 (0.168)	0.311 (0.068)	-0.123 (0.050)	0.206 (0.135)	-0.251 (0.132)	-0.048 (0.066)	-0.033 (0.168)	-0.092 (0.126)	0.068 (0.064)	-0.282 (0.088)	0.109 (0.071)	0.020 (0.052)
-0.177 (0.110)	1.608 (0.232)	-0.125 (0.065)	0.139 (0.148)	-0.605 (0.279)	0.114 (0.082)	0.170 (0.146)	-0.020 (0.157)	-0.081 (0.068)	-0.168 (0.108)	0.004 (0.094)	-0.061 (0.085)
0.056 (0.141)	0.021 (0.112)	0.352 (0.300)	0.065 (0.193)	0.117 (0.200)	0.205 (0.095)	0.090 (0.190)	-0.143 (0.213)	0.284 (0.089)	-0.248 (0.152)	0.010 (0.139)	-0.083 (0.095)
Variance – Covariance matrix of the estimated residuals: $V(\varepsilon_t) = \Lambda\Lambda^T$											
Λ			ω_{11} = 0.553 (0.031) ω_{21} = 0.257 (0.053) ω_{31} = 0.260 (0.071)			ω_{22} = 0.649 (0.036) ω_{32} = 0.157 (0.068)			Ω_{33} = 0.857 (0.048)		

Note: standard errors are presented in parenthesis; the order of autoregression p = 4 is chosen by Schwarz information criteria.

The estimated fractional differencing parameter is now very different in the UK and Japan compared to the US case. Specifically, it is equal to 0.615 for the UK, 0.568 for Japan, and 0.086 for the US (see Table 2). The unit root null is rejected in favour of mean reversion ($d < 1$) in the UK and the US at the 5% significance level and in Japan at the 10% level. On the other hand, the $I(0)$ null (i.e., $d = 0$) cannot be rejected for the UK and Japan at the 5% significance level and for the US at any level.

It is noteworthy that the results differ substantially from those obtained with the univariate methods. Whilst in the univariate case the unit root null hypothesis could not be rejected for any of the three series, it is decisively rejected in the multivariate context in favour of mean reversion. Moreover, the NAIRU hypothesis ($d = 0$), which was clearly rejected in the univariate models, cannot be rejected in the case of the US in the multivariate context. Since the multivariate model allows for correlations between the unemployment series, which are neglected in the univariate approach, more weight should be given to the multivariate results supporting the NAIRU hypothesis for the US and the "hysteresis" view for the UK and Japan, with a higher degree of persistence in the unemployment rate in the UK than in Japan.[7]

In order to corroborate the above results, we also conducted a small Monte Carlo experiment. We randomly generated three series of 164 observations (the same sample size as the one used in our application) and based on that we built three artificial series with an identical structure to the one presented in Table 2, i.e., with orders of integration of 0.615, 0.568 and 0.086 respectively for each of the series. We repeated the experiment 100 times, and then for each of the 300 simulated series we estimated on a univariate basis the order of integration using the three methods from Table 1 (i.e., parametric, semi parametric and non-parametric). The average estimates of d for each case are presented in Table 3. The results confirm those in Table 1 suggesting the superiority of the multivariate approach.

Table 3. Monte Carlo results based on a DGP with the values in Table 2

	Parametric Robinson (1994)	Semiparametric Robinson (1995)	Non-parametric Bloomfield (1973)
1st series	1.333	0.942	0.890
2nd series	1.037	0.835	0.654
3rd series	0.789	0.455	0.338

Note: 100 replications were used in each case.

V. Conclusions

This study revisits the issue of the degree of dependence in the unemployment series with the aim of discriminating between alternative unemployment theories. Specifically, it carries out both a univariate and multivariate analysis of the long

[7] This ranking of persistence is consistent with the univariate results: the UK displays the highest degree of dependence, followed by Japan and the US.

memory properties of the unemployment series in the UK, the US and Japan. The latter type of framework has the advantage of allowing for possible cross-country correlations overlooked in previous empirical studies. The results are indeed very different depending on whether a univariate or multivariate approach is taken, showing the importance of modelling cross-country correlations to draw valid inference.

The main findings can be summarised as follows. When taking a univariate approach, the unit root null cannot be rejected in case of the UK and Japanese unemployment series, and some degree of mean reversion ($d < 1$) is found in the case of the US unemployment rate. When applying multivariate methods instead, higher orders of integration are still found for the UK and Japanese series, but the NAIRU hypothesis cannot be rejected in the case of the US. Taking into account possible cross-country correlations is particularly important if business cycles are highly synchronized, since the unemployment rate tends to move along their swings.

A further issue is the possible presence of structural breaks. Many authors have shown that overlooking them produces bias in favour of $I(0)$ stationarity in the context of fractional integration (see, e.g., Granger and Teräsvirta 1999, Diebold and Inoue 2001, Gourieroux and Jasiak 2001, Granger and Hyung 2004, Jensen and Liu 2006, Perron and Qu 2006 and Charfeddine and Guégan 2012). We dealt with this issue by applying the method of Gil-Alana (2008) that estimates $I(d)$ with breaks, with the number of breaks and the break dates being endogenously determined by the model itself. The results (not reported) did not suggest the presence of any breaks in any of the individual series. Tests for structural breaks in multivariate $I(d)$ contexts are being developed and will be applied to the unemployment series in future papers.

Appendix

The Robinson (1994) univariate tests of fractional integration is presented here. The test statistic proposed in Robinson (1994) is based on the Lagrange Multiplier (LM) principle, and is given by

$$\hat{r} = \frac{T^{1/2}}{\hat{\sigma}^2} \hat{A}^{-1/2} \hat{a},$$

where T is the sample size and

$$\hat{a} = \frac{-2\pi}{T}\sum_{j=1}^{T-1}\psi(\lambda_j)\,g(\lambda_j;\hat{\tau})^{-1}\,I(\lambda_j); \qquad \hat{\sigma}^2 = \frac{2\pi}{T}\sum_{j=1}^{T-1}g(\lambda_j;\hat{\tau})^{-1}\,I(\lambda_j);$$

$$\hat{A} = \frac{2}{T}\left[\sum_{j=1}^{T-1}\psi(\lambda_j)^2 - \sum_{j=1}^{T-1}\psi(\lambda_j)\,\hat{\varepsilon}(\lambda_j)^T\left(\sum_{j=1}^{T-1}\hat{\varepsilon}(\lambda_j)\,\hat{\varepsilon}(\lambda_j)^T\right)^{-1}\sum_{j=1}^{T-1}\hat{\varepsilon}(\lambda_j)\,\psi(\lambda_j)\right];$$

$$\psi(\lambda_j) = \log\left|\,2\sin\frac{\lambda_j}{2}\right|;\ \hat{\varepsilon}(\lambda_j) = \frac{\partial}{\partial\tau}\log g(\lambda_j;\,\hat{\tau});\ \ \lambda_j = \frac{2\pi j}{T};\ \hat{\tau} = \operatorname{argmin}_{\tau\in T^*}\,\sigma^2(\tau),$$

where T^* is a compact subset of the R^q Euclidean space. $I(\lambda_j)$ is the periodogram of u_t evaluated under the null, and g is a known function related to the spectral density function of u_t, i.e., $f = (\sigma^2/2\pi)g$. Thus, if u_t is white noise, $g = 1$.

References

Alogoskoufis, George S., and Alan Manning (1988). On the persistence of unemployment. *Economic Policy* 7: 427-469.

Amable, Bruno, and Ken Mayhew (2011). Unemployment in the OECD. *Oxford Review of Economic Policy* 27: 207-220.

Barro, Robert (1988). The natural rate theory reconsidered: the persistence of unemployment. *American Economic Review, Papers and Proceedings* 78: 32-37.

Bianchi, Marco, and Gylfi Zoega (1998). Unemployment persistence: does the size of the shock matter? *Journal of Applied Econometrics* 13: 283-304.

Blanchard, Olivier J. (1999). Wage dynamics: reconciling theory and evidence. *American Economic Review, Papers and Proceedings* 89: 69-74.

Blanchard, Olivier J., and Lawrence H. Summers (1986). Hysteresis and the European unemployment problem. Working Paper 1950, NBER.

Blanchard, Olivier J., and Lawrence H. Summers (1987). Hysteresis in unemployment. *European Economic Review* 31: 288-295.

Blanchard, Olivier J., and Justin Wolfers (2000). The role of shocks and institutions in the rise of European unemployment: the aggregate evidence. *Economic Journal* 110: 1-33.

Bloomfield, Peter (1973). An exponential model in the spectrum of a scalar time series. *Biometrika* 60: 217-226.

Boes, Duan C., Richard A. Davis, and Sat N. Gupta (1989). Parameter estimation in low order fractionally differenced ARMA processes. *Stochastic Hydrology and Hydraulics* 3: 97-110.

Caporale, Guglielmo M., and Luis A. Gil-Alana (2007). Non-linearities and fractional integration in the US unemployment rate. *Oxford Bulletin of Economics and Statistics* 69: 521- 544.

Caporale, Guglielmo M., and Luis A. Gil-Alana (2008). Modelling the US, UK and Japanese unemployment rates: fractional integration and structural breaks, *Computational Statistics and Data Analysis* 52: 4998- 5013.

Charfeddine, Lanouar, and Dominique Guégan (2012). Breaks or long memory behaviour: An empirical investigation. *Physica A, Statistical Mechanics and its Applications* 391: 5712-5726.

Crato, Nuno, and Philip Rothman (1996). Measuring hysteresis in unemployment rates with long memory models. Working Paper, East Carolina University, Department of Economics.

Dahlhaus, Rainer (1989). Efficient parameter estimation for self-similar process. *Annals of Statistics* 17: 1749-1766.

Davidson, James, and Nigar Hashimzade (2009). Type I and type II fractional Brownian motions. A reconsideration. *Computational Statistics and Data Analysis* 53: 2089-2106.

Dickey, David, and Wayne Fuller (1979). Distribution of the estimators for autoregressive time series with unit root. *Journal of the American Statistical Association* 74: 427-431.

Diebold, Francis X., and Atsushi Inoue (2001). Long memory and regime switching. *Journal of Econometrics* 105: 131-159.

Fosten, Jack, and Atanu Ghoshray (2011). Dynamic persistence in the unemployment rate of OECD countries. *Economic Modelling* 28: 428-434.

Friedman, Milton (1968). The role of monetary policy. *American Economic Review* 58: 1-17.

Gil-Alana, Luis A. (2001). The persistence of unemployment in the USA and Europe in terms of fractionally ARIMA models. *Applied Economics*, 33:1263-1269.

Gil-Alana, Luis A. (2002). Modelling the persistence of unemployment in Canada. *International Review of Applied Economics* 16: 465-478.

Gil-Alana, Luis A. (2004). The use of the Bloomfield model as an approximation to ARMA process in the context of fractional integration. *Mathematical and Computer Modelling* 39: 29-426.

Gil-Alana, Luis A. (2008). Fractional integration and structural breaks at unknown periods of time. *Journal of Time Series Analysis* 29: 163-185.

Gordon, Robert J. (1989). Hysteresis in history. Was there ever a Phillips curve? *American Economic Review, Papers and Proceedings* 79: 220-225.

Gourieroux, Christian, and Joann Jasiak (2001). Memory and infrequent breaks. *Economics Letters* 70: 29-41.

Graafland, Johan J. (1991). On the causes of hysteresis in long term unemployment in the Netherlands. *Oxford Bulletin of Economics and Statistics* 53: 155-170.

Granger, Clive W.J., and Timo Teräsvirta (1999). A simple nonlinear time series model with misleading linear properties. *Economics Letters* 62: 161–165.

Granger, Clive W.J., and Namwon Hyung (2004). Occasional structural breaks and long memory with an application to the S&P 500 absolute stock return. *Journal of Empirical Finance* 11: 399-421.

Holl, Jürgen, and Robert M. Kunst (2011). Unit root in unemployment: new evidence from nonparametric tests. *Applied Economics Letters* 18: 509-512.

Hosoya, Yuzo (1996). The quasi-likelihood approach to statistical inference on multiple time-series with long-range dependence. *Journal of Econometrics* 73: 217-236.

Jensen, Mark and Ming Liu (2006). do long swings in the business cycle lead to strong persistence in output? *Journal of Monetary Economics* 53: 597–611.

King, Thomas B. and James Morley (2007). In search of the natural rate of unemployment. *Journal of Monetary Economics* 54: 550-564.

Leon-Ledesma, Miguel (2002). Unemployment hysteresis in the US states and the EU: A panel approach. *Bulletin of Economic Research* 54: 95-103.

Lobato, Ignacio and Carlos Velasco (2007). Efficient Wald tests for fractional unit roots. *Econometrica* 75: 575-589.

Lovcha, Yuliya and Alejandro Perez-Laborda (2014). The hours worked-productivity puzzle: identification in a fractional integration setting. *Macroeconomic Dynamics* available on CJO2014. doi: 10.1017/S1365100514000029.

Lopez, Humberto, Eva Ortega and Angel Ubide (1996). Explaining the dynamics of Spanish unemployment. Working Paper in Economics 96/14. European University Institute.

Marinucci, Domenico, and Peter M. Robinson (1999). Alternative forms of fractional Brownian motion. *Journal of Statistical Planning and Inference* 80: 111-122.

Mitchell, William F. (1993). Testing for unit roots and persistence in OECD unemployment rates. *Applied Economics* 225: 1489-1501.

Murray, Christian J., and David H. Papell (2000). Testing for unit roots in panels in the presence of structural change with an application to OECD unemployment. *Nonstationary Panels, Panel Cointegration, and Dynamic Panels. Advances in Econometrics* 15: 223-238. JAI Press.

Nickell, Stephen (1998). Unemployment: questions and some answers. *Economic Journal* 108: 802-816.

Nickell, Stephen, Jan Van Ours and Harry Huizinga (2000). The Netherlands and the United Kingdom: a European unemployment miracle? *Economic Policy* 30: 135-180.

Papell, David H., Christian J. Murray and Hala Ghiblawi (2000). The structure of unemployment. *Review of Economics and Statistics* 82: 309-315.

Perron, Pierre, and Qu, Zhongjun (2006). An analytical evaluation of the log-periodogram estimate in the presence of level shifts and its implications for stock returns volatility. Unpublished Manuscript. Department of Economics, Boston University.

Phelps, Edmund S. (1967). Phillips curve, expectations of inflation and optimal unemployment. *Economica* 34: 254-281.

Phelps, Edmund S. (1968). Money-wage dynamics and labor-market equilibrium. *Journal of Political Economy* 76: 678-711.

Phelps, Edmund S. (1994). *Structural slumps: The modern equilibrium theory of unemployment, interest, and assets*. Cambridge, MA, Harvard University Press.

Phelps, Edmund S. (1999). Behind this structural boom: the role of asset valuations. *American Economic Review: Papers and Proceedings* 89: 63-68.

Phillips, Peter C.B., and Pierre Perron (1988). Testing for a unit root in time series regression. *Biometrica* 75: 335-346.

Phillips, Peter C.B., and Zhijie Xiao (1999). A primer on unit root testing. *Journal of Economic Surveys* 12: 423-470.

Pissarides, Christopher (1990) *Equilibrium unemployment theory*. Oxford, Basil Blackwell.

Song, Frank M., and Yangru Wu (1998). Hysteresis in unemployment? Evidence from OECD countries. *Quarterly Review of Economics and Finance* 38: 181-192.

Robinson, Peter M. (1994). Efficient tests of nonstationary hypotheses. *Journal of the American Statistical Association* 89: 1420-1437.

Robinson, Peter M. (1995). Gaussian semi-parametric estimation of long range dependence. *Annals of Statistics* 23: 1630-1661.

Srinivasan, Naveen, and Pratik Mitra (2012). Hysteresis in unemployment: fact or fiction? *Economics Letters* 115: 419-422.

Strazicich, Mark C., Margie Tieslau, and Junsoo Lee (2001), Hysteresis in unemployment? Evidence from panel unit root tests with structural change. Mimeo. University of North Texas.

Tschernig, Rolf, and Klaus F. Zimmermann (1992). Illusive persistence in German unemployment. *Recherches Economiques du Lovaine* 58: 441-453.

Wilkinson, Gordon (1997). A micro approach to the issue of hysteresis in unemployment; evidence from the 1988-1990 labour market activity survey. Working Paper 97-12, Bank of Canada.