Unemployment persistence: Does the size of the shock matter?

Marco **Bianchi**
Bank of England
Monetary Analysis
Threadneedle Street
London, UK

Gylfi **Zoega**
Birkbeck College
Department of Economics
Gresse Street
London, UK

The views expressed are those of the author and do not necessarily reflect those of the Bank of England. The author thanks Alison Booth, David de la Croix, Jacques Drèze, Ron Smith, Dennis Snower and Howard Wall for helpful comments.

Issued by the Bank of England, London, EC2R 8AH to which requests for individual copies should be addressed: envelopes should be marked for the attention of the Publications Group. (Telephone: 0171–601-4030).

Bank of England 1996
ISSN 0142-6753

Contents

Abstract 5

1 Introduction 7

2 Two Measures of Persistence 9

3 The Econometric Methodology 11

3.1 Stability Tests 11

3.2 Nonparametric Analysis 12

3.3 Markov Switching Regressions 14

4 Regime Shifts in Unemployment Series 16

5 Conclusions 27

Appendix 30

References 32

Abstract

One of the stylized facts of unemployment is that shifts in its mean rate between decades and half–decades account for most of its variance. In this paper, we use a statistical analysis based on switching regression models and nonparametric density estimation techniques to identify the dates of infrequent changes in the mean of the unemployment rate series of 17 countries. We find that in most countries, unemployment persistence is small once the (infrequently) changing mean rate has been removed. The changes in the mean rate coincide with large annual changes in actual unemployment. We conclude that the observed persistence in unemployment appears to be consistent with hysteresis models which explain why unemployment hysteresis arises following *large* shocks to unemployment, but not following small changes. The result poses a challenge to theory since most existing hysteresis models do not have this non–linearity property.

1 Introduction

One of the stylized facts of postwar unemployment is that it has varied more between business cycles than within them. Thus, Layard, Nickell and Jackman (1991) have claimed that "*conventional business cycles account for relatively little of the history of unemployment*".[1] Blanchard and Summers (1987) have also pointed out that the degree of persistence may be caused primarily by abrupt changes in the mean rate of unemployment. Between such shifts unemployment may be stationary.

> *"Most of the time, equilibrium unemployment is stable, and unaffected by movements in the actual rate. But once in a while, a sequence of shocks pushes the equilibrium rate up or down, where it remains until another sequence dislodges it. Such infrequent changes appear to fit quite well with the empirical evidence of unemployment: unemployment seems indeed to be subject to infrequent changes in its mean level".*[2]

In spite of this observation, models of unemployment hysteresis appear to assume persistence in the unit–root sense and measure the persistence by the sum of coefficients in an autoregressive process with a constant (ie time invariant) mean value parameter. Many studies, including Sachs (1987), Summers (1990), Layard, Nickell and Jackman (1991), Bean and Layard (1988) and Karanassou and Snower (1993), have described the European unemployment problem as hysteresis measured by the coefficients of lagged unemployment in an ARMA(p, q) process. For this reason, most of the existing models of unemployment hysteresis are linear, that is changes in unemployment influence wage and price setting in a linear fashion. The insider–outsider model of Lindbeck and Snower (1986) is one example.

It is our objective in this paper to look at the time series properties of unemployment in order to draw out some of the stylized facts any theory of unemployment persistence, we believe, would have to take into

[1] Layard, R and Nickell, S and Jackman, R (1991), page 1.
[2] Blanchard, O J and Summers, L H (1987), pages 291-292.

account. We do not provide an explicit economic model which could account for any of the stylized facts nor do we estimate any particular model drawn from a well-defined economic theory. We focus on the time series properties of unemployment rates in different countries from a purely statistical point of view. Having said that, the results we find have implications for existing models of unemployment. In particular, we can argue whether any given model is consistent with our stylized facts.

We try to assess the significance of infrequent shifts in the mean rate of unemployment for 17 OECD countries. Using the switching regression model of Hamilton (1989, 1994), we identify the dates of the mean shifts in unemployment rates and remove their effects from the series. For the new series, we calculate the sum of the coefficients in the autoregressive process as a measure of persistence, and compare it to the same measure of persistence obtained when the mean shifts are not taken into account. We find that most of the persistence is accounted for by a few *large* shocks affecting the "equilibrium unemployment" rate, rather than a number of small shocks all having a persistent effect. We contrast two sources of unemployment persistence, that we define respectively as persistence due to a small number of infrequent (ie occasional) large shocks to unemployment causing shifts in its mean rate and persistence due to shocks in general, with no distinction between large and small shocks. As we shall see in Section 2, the two views imply different time series representations of unemployment data, and lead to different estimates of persistence.

The outline of the paper is as follows. In Section 2 we consider two different time series representations of unemployment rates implying different persistence of shocks. In Section 3 we summarise the econometric methodology which is then applied, in Section 4, to the unemployment rate series of 17 OECD countries. Section 5 concludes.

2 Two Measures of Persistence

The dominant approach in the mainstream literature assumes that the unemployment rate series x_t follows an autoregressive process of order p

$$x_t = \mu + \sum_{z=1}^{p} \rho_z x_{t-z} + e_t, \qquad e_t \sim \text{i.i.d.}(0, \sigma_e^2). \tag{1}$$

The sum of the autoregressive coefficients in the model, $P = \sum_{z=1}^{p} \rho_z$, is called "measure of persistence of unemployment". If $P = 1$, shocks (or innovations) e_t have permanent effects on the level of the series at *any* given point in time, for $t = 1, \ldots, T$. This notion of persistence in the sense of the series having a unit root is commonly referred to as "hysteresis in unemployment".[3] The following problem arises, however, with the pure and simple autoregressive representation of equation (1); whereas Blanchard and Summers refer to unemployment as being "*subject to infrequent changes in its mean value*" in our starting quote, the mean level of unemployment in (1), μ, is fixed over time. Thus, the conventional definition of unemployment persistence fails to distinguish between the persistence of different shocks by taking into account *the possibility of large shocks changing the model parameters.*

The definition of unemployment persistence that we propose in this paper is broader than the conventional as it allows the mean rate of unemployment to change abruptly over time. A time series representation of the unemployment data consistent with our view is

$$x_t = \mu_i(S_j) + \sum_{z=1}^{q} \rho'_z x_{t-z} + e'_t, \qquad e'_t \sim \text{i.i.d.}(0, \sigma_{e'}^2), \tag{2}$$

$$\pi(i) + 1 \leq t \leq \pi(i+1), \quad i = 0, 1, \ldots, n, \quad j = 1, \ldots, m, \quad m \leq n + 1,$$

where: m is the number of states in unemployment (for example, a state of low unemployment and a state of high unemployment); μ_i is the mean value of unemployment, depending on the state S_j, in the

[3] See Blanchard, O J and Summers, L H (1987), Lindbeck, A and Snower, D J (1986).

subsample $\pi(i)+1$ to $\pi(i+1)$, with $\pi(0) \equiv 0$ and $\pi(n+1) \equiv T$; n is the number of mean shifts in the series as the result of large shocks occurring infrequently at time $\pi(1), \ldots, \pi(n)$. In the following, we call the time series representation of equation (2) the "*shifting mean value*" (SMV hereafter) model.

We now draw attention to the following economic interpretation of the SMV model: whenever sudden, abrupt shifts occur in the model parameters, we tend to attribute these shifts to *structural changes*, or *large shocks*, in the economy. Thus, even if we cannot exclude the possibility that large shocks may not necessarily imply a mean shift in the series (ie large shocks can also have transitory effects), we assume that a mean shift is always observed as the result of a large shock. This interpretation is similar to that of Perron (1989).[4]

The SMV model represents a useful generalisation of equation (1) in the following sense. If there is only one state (equilibrium) in the series, the mean unemployment rate μ is constant over the sample period, rather than infrequently changing; equation (2) collapses into the pure and simple autoregressive model of equation (1). In fact, $m = 1$ implies that $n = 0$, $\mu_i = \mu$, $q = p$, $\rho'_z = \rho_z$, $P' = \sum_{z=1}^{q} \rho'_z = P$. If there is more than one state in the series, however, there are genuine regime shifts in unemployment. The part of persistence captured by the shifting parameter $\mu_i(S_j)$ is removed from the autoregressive process, and we have $P' < P$. Thus, as opposed to the pure and simple autoregressive model of equation (1), we define $P' = \sum_{z=1}^{q} \rho'_z$ as a measure of the persistence which is left in the series after removing the effects of infrequent changes in the mean at $\pi(1), \ldots, \pi(n)$.

In the context of an empirical analysis, both time series representations (1) and (2) aim at obtaining an estimate of the persistence of shocks: however, whereas the mainstream model only requires the estimation of a simple autoregressive process, the switching regression model of equation (2) requires first an estimation of the number of states in the

[4] There, a large negative shock like the Great Crash in 1929 causes a sudden drop in the intercept value of the US GNP trend.

unemployment series m as well as an estimation of the number of regime shifts n and the dating of the regime shifts $\pi(1), \ldots, \pi(n)$.

3 The Econometric Methodology

Bearing in mind the time series representations of unemployment rates described in the previous section, we can summarise our econometric methodology as follows. First, we check the validity of the assumption of time invariant parameters implicit in the traditional view of unemployment persistence by means of standard stability tests based on recursive least squares. Subsequently, we use nonparametric density estimation and the bootstrap methodology to test for the number of states (m) in the density of the frequency distribution of unemployment rate series. Finally, for a given number of states, we estimate a switching regression model (Hamilton, 1989) to detect the timing of the shift points. We separately turn to these issues in the following subsections.

3.1 Stability Tests

A natural procedure to check the validity of the pure and simple autoregressive model of unemployment persistence is to perform a stability test on the results obtained from the estimation of equation (1). In the absence of structural changes, the estimated parameters are time invariant and we would not reject the stability hypothesis. If this is not the case, then we can reject the traditional autoregressive representation of unemployment, whereas we cannot exclude the SMV representation of equation (2).

Stability tests are based on recursive least squares where the parameters in the regression are estimated repeatedly, using ever larger subsets of the sample data. The recursive residual is defined as

$$\mathbf{w}_t = \frac{\mathbf{x}_t - \mathbf{z}_t' \mathbf{b}_{t-1}}{\sqrt{1 + \mathbf{z}_t'(\mathbf{Z}_{t-1}'\mathbf{Z}_{t-1})^{-1}\mathbf{z}_t}}, \quad t = k+1, \ldots, T \tag{3}$$

where $\mathbf{Z}_{t-1}$ denotes the $(t-1) \times k$ matrix of regressors from period 1 to period $t-1$; $\mathbf{x}_t$ the corresponding vector of observations of the dependent

variable; $\mathbf{b}_{t-1}$ the corresponding vector of estimated coefficients; $\mathbf{z}_t'$ the row vector of observations on the regressors in period t. A stability test on the recursive residuals is simply obtained by plotting the residuals together with plus and minus two standard error bands; residuals outside the bands indicate instability in the equation parameters.

3.2 Nonparametric Analysis

Stability tests can reject the pure and simple autoregressive model of equation (1). To inspect the correctness of the SMV model representation for unemployment data we use, instead, nonparametric methods. The basic argument for this type of analysis is that the occurrence of regime shifts in time series is reflected in a mixture distribution; in the presence of regime shifts, the density of the frequency distribution of the unemployment rate series should be multimodal, with the number of modes in the density corresponding to the number of states in the series. A test for multimodality is obtained by combining kernel density estimation with bootstrap methods.

In the presence of m^* states, the density of the frequency distribution of a series generated by (2) can be expressed by a mixture of distributions

$$f(x) = \sum_{j=1}^{m^*} p_j \cdot g_j(x; \mu(S_j), \sigma^2(S_j)), \tag{4}$$

where p_j's are mixture proportions with $\sum_{j=1}^{m^*} p_j = 1$, and g_j are unimodal densities with first and second moments $\mu(S_j)$ and $\sigma^2(S_j)$. Assuming that the differences in the centrality parameters $\mu(S_j)$'s are "large" relative to the dispersion parameters $\sigma^2(S_j)$'s, equation (4) implies that $f(x)$ is multimodal with m^* modes.[5]

[5] The modes of the density are said to be "well–separated" in this case. A particular case of this situation occurs for example when σ^2 is constant over time (that is when $\sigma^2(S_j) = \sigma^2$ for every $j = 1, \ldots, m^*$). It is also worth remembering that even though kernel density estimators were primarily developed for independent and identically distributed observations, some theoretical work has shown the consistency of these estimators with dependent data [see for instance Györfi, Härdle, Sarda and Vieu (1989), pages 66–79].

By the kernel method, the density of x is estimated nonparametrically by (see Silverman, 1986; Härdle, 1990)

$$\hat{f}(x) = (Th)^{-1} \sum_{t=1}^{T} K\left(\frac{x - x_t}{h}\right) = (Th)^{-1} \sum_{t=1}^{T} K(u), \tag{5}$$

where h is the bandwidth and $K(u)$ is the Gaussian kernel

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right). \tag{6}$$

The crucial concept for the detection of the number of states using kernel density estimators in our framework is the concept of *critical bandwidth* (Silverman 1981, 1983, 1986). A critical bandwidth $h_{crit}(m)$ is defined as the smallest possible h producing a density with at most m modes, which means that for all $h < h_{crit}(m)$ the estimated density $\hat{f}_h$ has at least $m + 1$ modes. Bandwidth $h > 0$ governs the degree of smoothness of the density estimate, that is with small values of h wiggly estimates showing spurious structure in the data can often be obtained; with big values of h, on the contrary, important features of the underlying density can be smoothed away. Thus, in the absence of regime shifts, $m^* = 1$, ie the correct value of the bandwidth is $h = h^* \geq h_{crit}(1)$. In the presence of regime shifts, however, there must be at least two states (or regimes) towards which the series can switch.

In order to assess the number of modes in the density (i.e states in the series), $h_{crit}(m)$ can be used as a statistic to test

$$H_0\colon f(\tilde{x}) \text{ has } m \text{ modes} \quad \text{vs} \quad H_1\colon f(\tilde{x}) \text{ has more than } m \text{ modes.} \tag{7}$$

A 'large' value of $h_{crit}(m)$ indicates more than m modes, thus rejecting the null.[6] How large is large in this context is assessed by the bootstrap, as discussed by Silverman in a number of papers, and, among others, by Efron and Tibshirani (1993) and Izenman and Sommer (1988).[7] The null

[6] In fact, suppose that the true underlying density has two modes; then, a large value of $h_{crit}(1)$ is expected, because a considerable amount of smoothing is required to obtain a unimodal density estimate.

[7] See also the Appendix for a summary.

hypothesis that there are m modes in the density is not rejected versus the alternative of more than m modes whenever the p-value is larger than a given critical value. Silverman (1983) has shown theoretically why the bootstrap test may tend to be conservative with respect to the null hypothesis (ie to underestimate the number of modes in the density) if standard p-values of 0.05 or 0.10 are employed. In the absence of published simulation studies on Silverman's test, Izenman and Sommer have recommended a critical value of approximately 0.40 (see Izenman and Sommer, 1988, page 948).

3.3 Markov Switching Regressions

Nonparametric density estimation represents a useful tool for an exploratory investigation of the data, in particular tests for multimodality in the density of the frequency distribution of the unemployment rate series. In order to make inference about the dating of the regime shifts, a popular parametric procedure for estimating a changing mean process involving mixtures of normal distributions is the Markov switching regression model of Hamilton (1989, 1994). The coefficients change with an unobserved indicator S_t according to

$$\begin{aligned} x_t - \mu(S_t) &= \phi_1[x_{t-1} - \mu(S_{t-1})] + \phi_2[x_{t-2} - \mu(S_{t-2})] + \cdots \\ &+ \phi_q[x_{t-q} - \mu(S_{t-q})] + \sigma(S_t)\epsilon_t, \end{aligned} \tag{8}$$

where the mean μ and the standard deviation σ of the process depend on S_t, the regime or state at time t, and $\epsilon_t \sim N(0,1)$. S_t is an indicator variable which follows a Markov chain with transition probabilities

$$\Pr(S_t = j | S_{t-1} = i) = p_{ij}, \quad i, j = 1, \ldots, m$$

The state-dependent means and standard deviations are specified as:

$$\mu(S_t) = \alpha_0 + \alpha_1 S_{1t} + \alpha_2 S_{2t} + \cdots + \alpha_m S_{mt} \tag{9}$$

$$\sigma(S_t) = \omega_0 + \omega_1 S_{1t} + \omega_2 S_{2t} + \cdots + \omega_m S_{mt} \tag{10}$$

where $S_{it} = 1$ when $S_t = i$, and zero otherwise. Substituting equations (9) and (10) into equation (8), we have

$$\begin{aligned} x_t &= \alpha_0 + \alpha_1 S_{1t} + \alpha_2 S_{2t} + \cdots + \alpha_m S_{mt} + z_t \\ z_t &= \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_q z_{t-q} \\ &+ (\omega_0 + \omega_1 S_{1t} + \omega_2 S_{2t} + \cdots + \omega_m S_{mt}) \cdot \epsilon_t. \end{aligned} \tag{11}$$

The parameters α, ω, ϕ and the transition probabilities p_{ij}, which can be estimated by maximum likelihood, allow us to derive the sequence of joint conditional probabilities (conditional upon the information available at time t) of being in state i, j $(i, j = 1, 2)$ at times t, $t-1$, $t-2$, denoted by $p(S_t, S_{t-1}, S_{t-2} | x_t, x_{t-1}, \ldots, x_0)$. The probabilities of being in state 1 or 2 at time t, called *filter probabilities*, are next obtained by summing the joint conditional probabilities

$$p(S_t | x_t, x_{t-1}, \ldots, x_0) = \sum_{S_{t-1}=0}^{2} \sum_{S_{t-2}=0}^{2} p(S_t, S_{t-1}, S_{t-2} | x_t, x_{t-1}, \ldots, x_0). \tag{12}$$

The filter probabilities deliver information about the regime in which the series is most likely to be at every point in the sample; thus, they provide an effective tool for dating the various switches in the series.[8]

[8] It is useful to recall that switching regression models can be fitted to the data for a given number of states. If the number of states has not to be chosen arbitrarily, testing for the number of states in the context of Markov switching regression models raises a particular problem known in the statistics literature as hypothesis testing when a nuisance parameter is not identified under the null hypothesis (see, among the others, Garcia and Perron, 1991). This is often called the "*identification problem*". Although some statistical tests have been proposed in the literature to manage this case (Gallant, A R (1977)), the identification problem in statistics remains a difficult topic. Thus, it makes sense here to use a purely nonparametric method like the bootstrap in helping to fix the number of states, m.

4 Regime Shifts in Unemployment Series

In this section we proceed to estimate the two measures of unemployment persistence mentioned in Section 2 for 17 OECD countries. These include Austria (AUS), Australia (AUT), Belgium (BE), Canada (CA), Denmark (DE), Germany (GE), Finland (FI), France (FR), Ireland (IRE), Italy (IT), Japan (JA), the Netherlands (NE), Norway (NOR), Spain (SP), Sweden (SW), the United Kindgom (UK) and the United States (US). For all countries, data consist of annual observations covering the period 1960–1993. The series are plotted in Figure 1.

Following the econometric methodology discussed in Section 2, we first estimate for all countries a pure and simple autoregressive process of order p (where p is the number of statistically significant lags) and check for the stability of the regressions. The plots of the recursive residuals with plus and minus two standard error bands exibited in Figure 2 indicate that for virtually all countries (with, maybe, the only exception being the United States), the stability hypothesis is clearly rejected.[9]

[9]For some countries, like Finland, Norway and Sweden, the rejection appears to reflect the dramatic changes in the series in recent years. For reasons of space, results for Norway have been set in the Appendix.

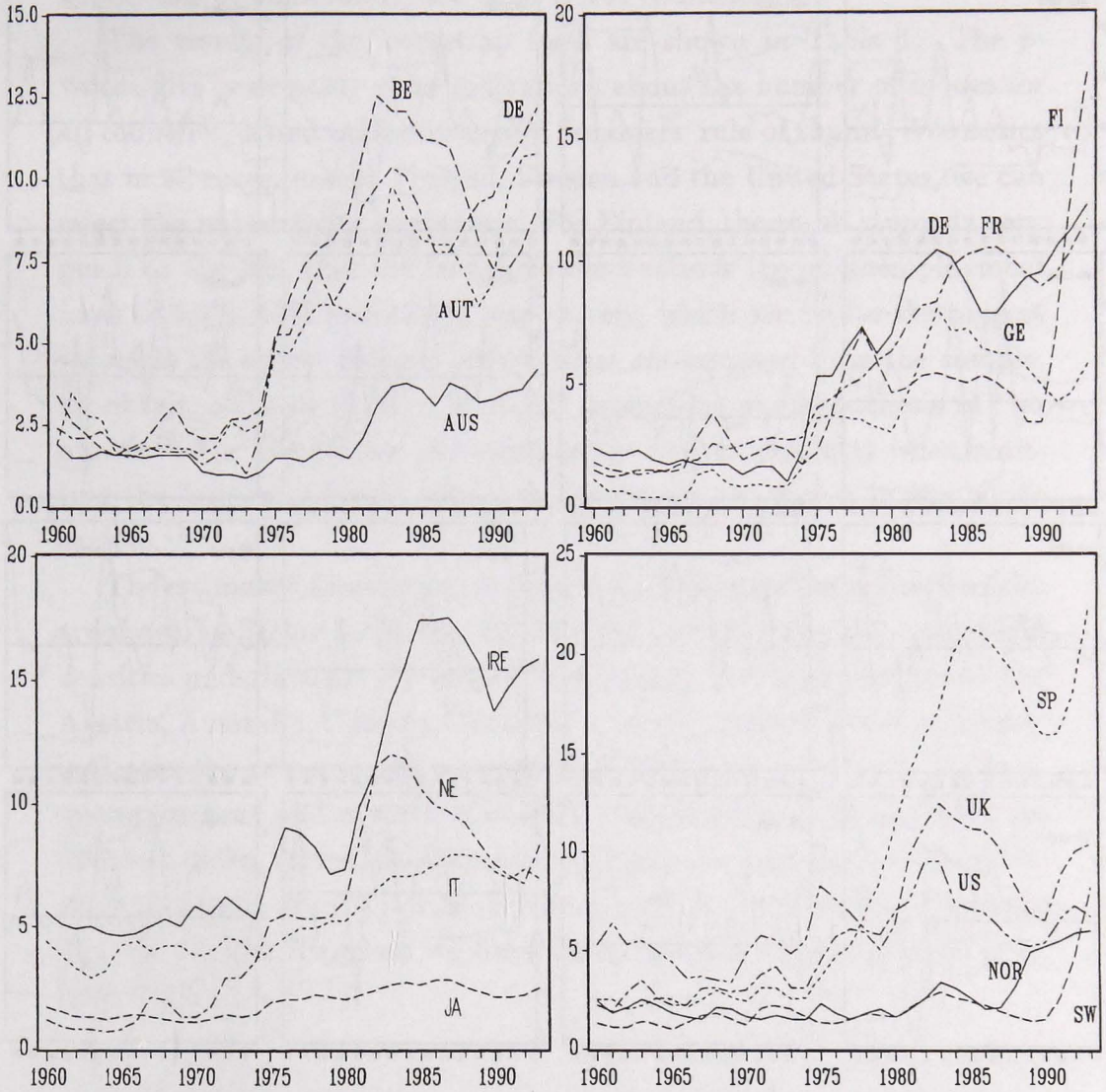

Figure 1: Standardised unemployment rates in 17 countries from 1960 to 1993. Source: *OECD Economic Outlook*.

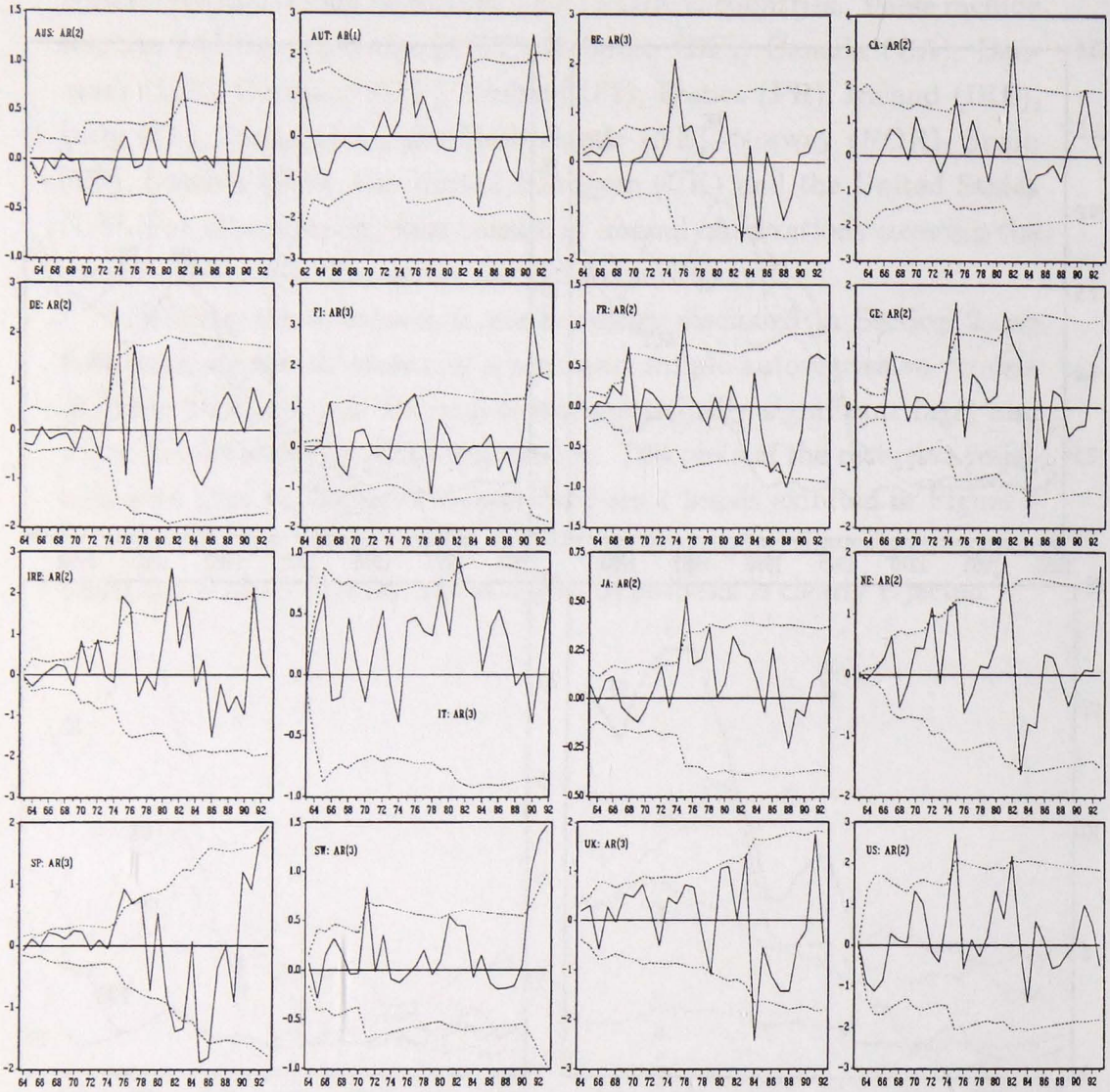

Figure 2: Recursive residuals with plus and minus two standard errors, obtained when fitting autoregressive processes to the series of unemployment rates.

For this reason, we consider next the nonparametric estimation of the density of the frequency distribution of the different series; here, if the results of the stability tests are to be confirmed, we should reject the hypothesis of unimodality for most of the countries.

The results of the bootstrap tests are shown in Table 1. The p-values give reasonably clear indications about the number of modes for all countries, based on Izenman and Sommers' rule of thumb. We notice that in all cases, except Finland, Sweden and the United States, we can reject the unimodality hypothesis. For Finland, the result depends very much on the fact that the last three observations report unemployment rates of 7.5%, 13% and 17.7% respectively, which are by far the biggest values in the series; if these observations are removed from the sample, we obtain p-values (0.04, 0.35, 0.35) supporting the hypothesis of two modes.[10] For Sweden, on the contrary, we find unimodality when omitting the last three observations, as for the United States in the whole sample.[11]

The estimated densities consistent with the detected number of modes are shown in Figure 3. For the United States and Sweden*, the unimodal densities underline the presence of a single regime of unemployment. For Austria, Australia, Canada, Denmark, Finland*, France, etc., bimodality indicates the presence of two unemployment regimes, a state of "low" unemployment and a state of "high" unemployment, characterised by different mean values. In the case of Japan, for example, we have two modes centered at $\mu(S_1)$=1.3% and $\mu(S_2)$=2.2%. For Belgium, Germany and the United Kingdom we have three states of unemployment (low, high, higher).

[10] The three large observations make density estimation more difficult by generating a region on the real line where data points are very sparse. This affects the results because a global bandwidth h is used to smooth the data locally. Obtaining more precise results would require, in this case, to smooth the density less in those regions where data points are more sparse, and smoothing it more in those regions where data points are dense, thus using a "local varying" bandwidth.

[11] In the remainder of the paper we will denote by Finland* and Sweden* the unemployment series from 1960–1990. We will refer to Finland and Sweden (without the '*' symbol) as the unemployment series in the whole sample.

Country	Critical Bandwidths			p-values				
	$h_{crit}(1)$	$h_{crit}(2)$	$h_{crit}(3)$	$m=1$	$m=2$	$m=3$	m^*	h^*
US	0.64	0.55	0.52	0.36	0.16	0.03	1	0.65
Austria	0.79	0.20	0.11	0.01	0.40	0.93	2	0.25
Australia	1.98	0.85	0.57	0.05	0.50	0.40	2	0.90
Canada	1.13	0.62	0.47	0.30	0.76	0.54	2	0.70
Denmark	3.13	0.71	0.36	0.00	0.82	0.98	2	0.80
Finland	2.30	2.10	1.10	0.32	0.00	0.04	1	2.30
Finland*	1.10	0.50	0.40	0.04	0.35	0.35	2	0.55
France	2.66	1.00	0.67	0.01	0.17	0.18	2	1.10
Ireland	3.58	0.90	0.46	0.02	0.62	0.99	2	1.00
Italy	1.04	0.31	0.16	0.05	0.57	0.98	2	0.40
Japan	0.43	0.17	0.11	0.00	0.29	0.15	2	0.25
Netherlands	1.83	1.10	0.81	0.29	0.40	0.28	2	1.20
Norway	0.97	0.28	0.27	0.01	0.59	0.15	2	0.40
Spain	5.67	2.13	1.43	0.01	0.17	0.09	2	2.20
Belgium	2.83	1.42	0.72	0.01	0.09	0.24	3	0.80
Germany	1.39	1.16	0.47	0.14	0.00	0.45	3	0.60
Sweden	1.50	0.68	0.20	0.00	0.07	0.41	3	0.25
Sweden*	0.15	0.12	0.11	0.95	0.62	0.20	1	0.20
UK	1.92	0.97	0.65	0.16	0.34	0.40	3	0.70

Table 1: Bootstrap multimodality tests. Finland* and Sweden* report the results of the test on the data up to 1990. Note: $h^* \geq h_{crit}(m^*)$.

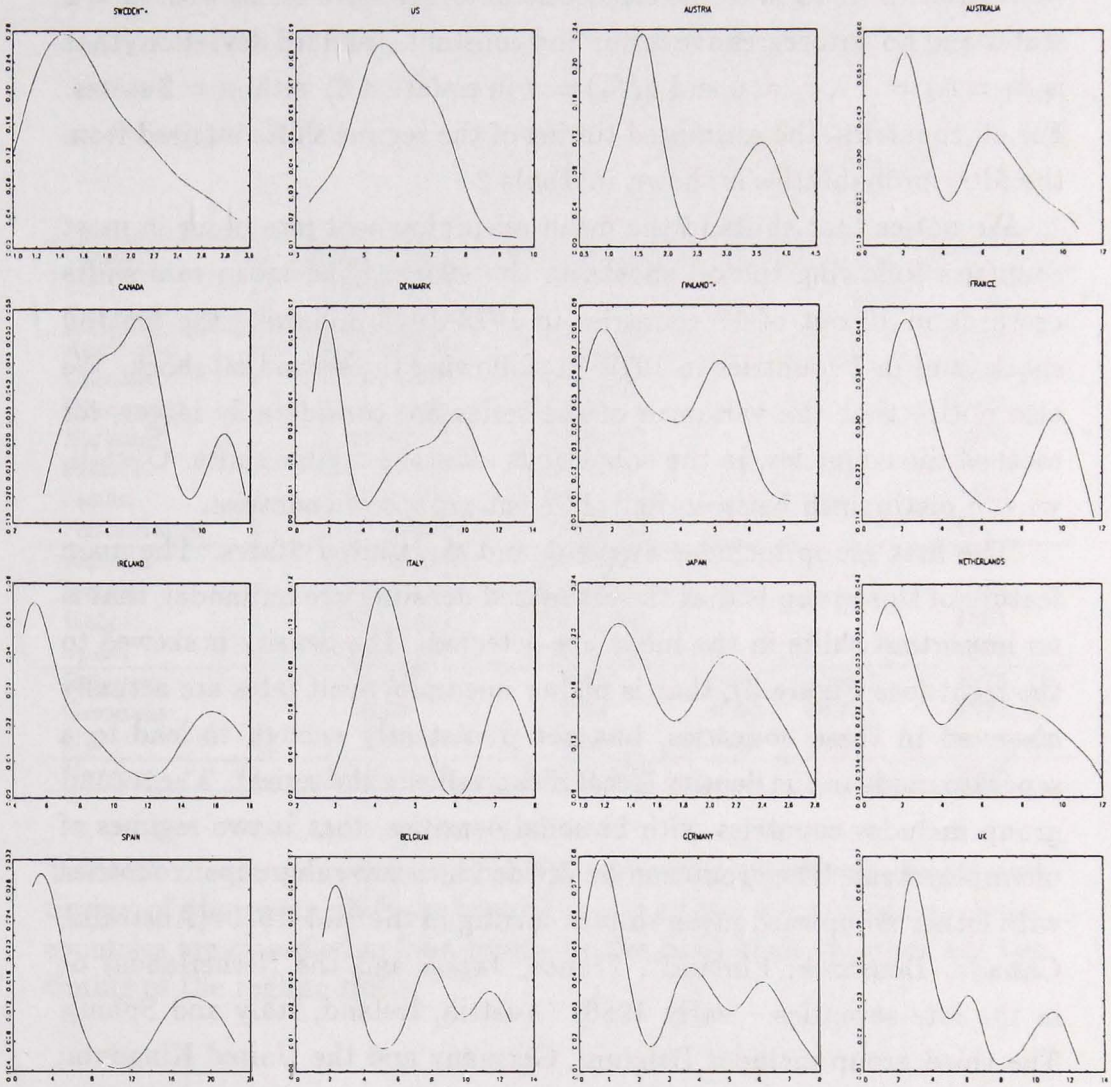

Figure 3: Density estimates obtained using a bandwidth determined by bootstrap multimodality tests (reported in the last column of Table 1).

We estimate next the switching regression model with a number of states, m, equal to the number of modes detected by the bootstrap tests (see Table 1). Given the small number of observations ($T = 34$), we restrict estimation to the case of no autoregressive terms with $m = 2$ states and no autoregressive terms and constant standard deviation (that is $\phi_1 = \phi_2 = \ldots, \phi_q = 0$ and $\sigma(S_t) = \sigma$ in equation 8) with $m = 3$ states. For all countries, the estimated timing of the regime shifts inferred from the filter probabilities is shown in Table 2.

We notice that shifts in the mean unemployment rate occur in most countries following the oil shocks in the 1970s. The mean rate shifts upwards in 10 out of 17 countries in 1973–1975, following the first oil shock, and in 7 countries in 1979–81, following the second oil shock. We also notice that the variances of the series are considerably larger, for most of the countries, in the subperiods after the regime shifts. Overall, we can distinguish between four different groups of countries.

The first group includes Sweden* and the United States. The main feature of this group is that the estimated densities are unimodal, that is no important shifts in the mean are detected. The density is skewed to the right (see Figure 3), that is higher unemployment rates are actually observed in these countries, but not persistently enough to lead to a separate mode in the density (local mean value in the series). The second group includes countries with bimodal densities, that is two regimes of unemployment. The group can be divided into two subgroups: countries with either an upward mean shift occurring in the mid–1970s (Australia, Canada, Denmark, Finland*, France, Japan and the Netherlands) or in the late seventies – early 1980s (Austria, Ireland, Italy and Spain). The third group includes Belgium, Germany and the United Kingdom; these countries have trimodal densities suggesting the presence of three local mean values in the unemployment rate series. In this group the mean rate of unemployment shifted upwards in both the mid and the late 1970s. The fourth group includes Scandinavian countries, Norway, Sweden, and Finland characterised by regime shifts occurring in the late 1980s – early 1990s.

Country	m	$\hat{\mu}(S_1), \hat{\sigma}^2(S_1)$	$\hat{\mu}(S_2), \hat{\sigma}^2(S_2)$	$\hat{\mu}(S_3)$	$\hat{\sigma}^2$	Dates
US	1	6.02 (2.33)				
Sweden*	1	5.94 (2.47)				
Australia	2	2.15 (0.30)	7.39 (3.37)			1974
Canada	2	6.21 (1.13)	10.8 (2.60)			1975
Denmark	2	1.82 (0.13)	8.57 (3.69)			1974
Finland*	2	2.03 (0.51)	4.29 (0.90)			1975
France	2	2.07 (0.33)	8.16 (5.32)			1974
Japan	2	1.31 (0.02)	2.31 (0.08)			1974
Netherlands	2	1.44 (0.52)	7.79 (6.16)			1973
Austria	2	1.48 (0.08)	3.54 (0.09)			1981
Ireland	2	6.17 (2.37)	15.4 (3.21)			1981
Italy	2	4.24 (0.45)	7.25 (0.30)			1981
Spain	2	3.36 (2.80)	17.8 (9.10)			1979
Belgium	3	2.68	8.05	10.1	(1.91)	1975, 79
Germany	3	0.81	3.54	6.00	(0.52)	1974, 81
UK	3	2.97	5.66	9.84	(1.50)	1974, 80
Norway	2	2.06 (0.27)	5.50 (0.17)			1988

Table 2: Parameter estimates in the switching regression model and timing of the mean shifts inferred from the filter probabilities. Note: countries are classified in four groups on the basis of the number and the timing of the regime shifts.

For all countries (except Norway for which, again, results are presented in the Appendix for reasons of space), Figure 4 shows the plot of the unemployment rate series, its local mean value and the dates of the regime shifts. The figure indicates that the SMV model well represents the observed time series behaviour of actual unemployment rates in most countries. It is only for France, Italy and Spain that the goodness of fit of the model does not appear to be very satisfactory. For these countries, indeed, the SMV model may not be appropriate, and a more general model should perhaps be considered by replacing equation (2) with: $x_t = \mu_i(S_j)t + \beta_i(S_j) + \sum_{z=1}^{q} \rho'_z x_{t-z} + e'_t$, with $e'_t \sim$ i.i.d.$(0, \sigma^2_{e'})$. This would allow for infrequent changes in both the trend intercept and slope parameters, rather than simply infrequent jumps in the mean value of the series.

After having detected the dates of the shift points, the question arises how much persistence remains in the unemployment series once the shifts in the mean, that we associate with the occurrence of *large* shocks, have been removed from the series. To analyse this, we calculate the two measures of persistence P and P' defined in Section 2, implied by the time series representations of equations (1) and (2). The results are shown in Table 3. For all countries, the sum of the coefficients in the autoregression is considerably smaller when the mean shifts are accounted for, indicating that infrequent shifts in the mean rate of unemployment seem to capture a lot of the persistence in unemployment.

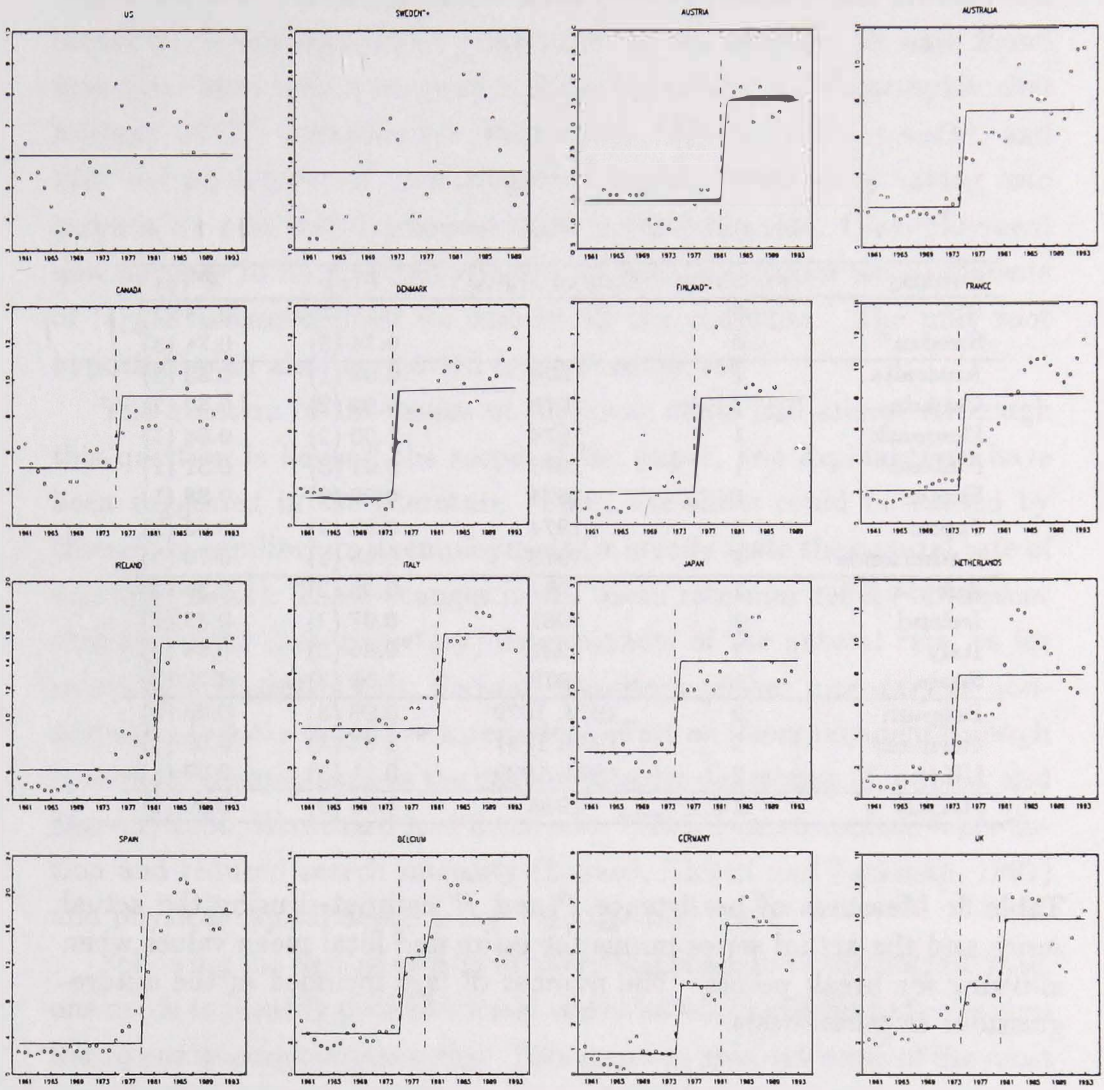

Figure 4: Actual unemployment rates, dates of regime shifts and mean unemployment rate within subsamples (ie before and after the switches in the mean).

Country	No. Shifts	Date of Shifts	$\hat{P}(p)$	$\hat{P}'(q)$
US	0	-	0.75 (2)	0.75 (2)
Sweden*	0	-	0.74 (3)	0.74 (3)
Australia	1	1974	0.99 (1)	0.58 (2)
Canada	1	1975	0.90 (2)	0.52 (2)
Denmark	1	1974	1.00 (2)	0.84 (1)
Finland*	1	1975	0.91 (3)	0.31 (2)
France	1	1974	0.99 (2)	0.88 (1)
Japan	1	1974	0.93 (2)	0.65 (2)
Netherlands	1	1973	0.95 (2)	0.70 (2)
Austria	1	1981	0.96 (2)	0.36 (2)
Ireland	1	1981	0.97 (2)	0.45 (1)
Italy	1	1981	0.96 (3)	0.54 (1)
Spain	1	1979	1.01 (3)	0.29 (2)
Belgium	2	1975, 1979	0.96 (3)	0.66 (1)
Germany	2	1974, 1981	0.93 (2)	0.59 (1)
UK	2	1974, 1980	0.95 (3)	0.57 (2)
Norway	1	1988	1.06 (3)	0.46 (1)

Table 3: Measures of persistence P and P' estimated using the actual series and the actual series minus the estimated local mean values when allowing for break points. The number of lags included in the autoregressions in parenthesis.

5 Conclusions

The distinction between the persistence of large and small shocks is an important issue which appears to have been neglected in the mainstream literature on unemployment persistence. In our analysis, we have found that there have been infrequent shifts in the mean rate of unemployment in most OECD countries following either 1974 or 1979 (or both), and that the persistence of unemployment is much reduced by taking into account the relatively infrequent shifts in the mean rate. Unemployment now appears to be a stationary process with low values for coefficients of lagged unemployment for almost all the countries. The unit root hypothesis can also be rejected in most countries.[12]

The question of the causes of the mean shifts still arises. Although this question is beyond the scope of the paper, two explanations have been suggested in the literature. First, the shifts could be caused by changes in equilibrium unemployment (in steady state the natural rate of unemployment). These changes in the mean rate may reflect infrequent changes in the (non-monetary) determinants of the natural rate, as for example in Phelps (1994). Second, transitory (either monetary or non-monetary) shocks may have a persistent effect on unemployment through hysteresis channels such as the insider-outsider distinction (Lindbeck and Snower, 1986; Blanchard and Summers, 1986), human capital depreciation and reduced search intensity (Layard, Nickell and Jackman, 1991) and physical capital depreciation (Modigliani, 1987).

Following the first approach of modelling changes in the natural rate, one needs to identify possible causal variables which exhibit patterns similar to our unemployment series. This seems to rule out some of the most frequently suggested variables, such as changes in the duration and level of unemployment benefits or in the rate of social security and income taxes. But changes in energy prices do exhibit a similar pattern with the mean rate changing in the mid and late 1970s. Also, as suggested by Phelps (1994), world real interest rates do rise significantly in the early

[12] Test statistics are available from the authors.

1980s thus opening up the possibility that they exert an impact on the natural rate.[13]

From the perspective of models of unemployment hysteresis, it can be concluded from the shifting-mean-value model that some shocks to unemployment appear to have a more persistent effect than others. From the data we can infer that the shifts in mean unemployment coincide with some of the largest single annual changes in the rate of unemployment. In other words, large shocks may be more likely to trigger changes in the mean rate of unemployment than small shocks. However, we also note that some large increases in unemployment did not persist, the best example of which is the US experience in the early 1980s.

A problem with existing models of unemployment hysteresis, from our perspective, is that they are linear,[14] that is they do not imply that large and small changes in unemployment differ in duration. In particular, changes in the rate of unemployment, which are supposed to capture human capital and insider-outsider effects, appear linearly in wage- and price-setting equations in Layard, Nickell and Jackman (1991). More generally, in the insider-outsider models, for example, persistence is a function of the size of hiring and firing costs and of insiders' bargaining power, but not a function of the size of the initial change in unemployment.[15] If the SMV model considered in this paper is accepted as a good representation of unemployment behavior for most OECD countries, it seems that theory must be modified to better account for the empirical evidence on unemployment.

In the past, much effort has gone into explaining the statistical significance of lags in unemployment equations. We conclude that some of

[13] Bianchi, M and Zoega, G (1994).

[14] This explains the emphasis put on lags in the empirical studies of unemployment hysteresis. See eg Karanassou, M and Snower, D J (1993) and Layard, R and Nickell, S and Jackman R (1991).

[15] Models of multiple equilibria, such as Manning, A (1990), appear to be promising. Here increasing returns cause the labour–curve to slope upwards. Other models, like those with linear adjustment costs such as Bentolila, S and Bertola, G (1990), predict that small labour demand shocks affect employment less than large ones. These models do not predict, however, that small changes in unemployment are less persistent than larger ones.

this effort may have been partly misguided and that instead one should analyse economic relationships at work during periods of large changes in unemployment coinciding with an apparent shift from one equilibrium to another.

Appendix

Results for Norway.

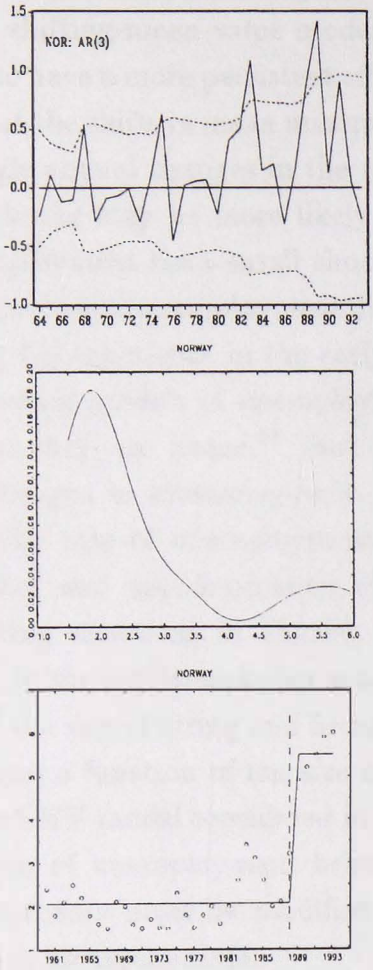

Figure 5: Results for Norway. Stability test on the recursive residuals of an AR(3) process (top), density estimate consistent with bimodality (center) and actual and fitted values with a break point in 1988.

Bootstrap Multimodality Tests.

Given the actual series $\mathbf{x} = (x_1, \ldots, x_T)'$, a sample $\mathbf{y}^* = (y_1^*, \ldots, y_T^*)'$ is obtained by resampling with replacement from $\mathbf{x}$. To ensure that the realisations obtained from the bootstrap have the same first and second moment properties of the observations $\mathbf{x}$, the following transformation is considered

$$x_t^* = \bar{y}^* + \left(1 + \frac{h_{crit}^2(m)}{s^2}\right)^{-1/2} (y_t^* - \bar{y}^* + h_{crit}(m)e_t), \quad t = 1, 2, \ldots, T, \tag{13}$$

where $\bar{y}^* = \text{mean}(\mathbf{y}^*)$, s^2 is the sample variance of $\mathbf{x}$, and e_t standard normal variables generated by the computer. A p-value for $h_{crit}(m)$, which is sometimes called the 'achieved significance level' (ASL) of the test, is obtained by generating a large number of samples from $f_{crit}(m)$ and counting the proportion of samples for which $h_{crit}^*(m) > h_{crit}(m)$, where $h_{crit}^*(m)$ is the smallest value of h producing a density estimate with m modes from the bootstrap data $\mathbf{x}^*$. We have formally

$$ASL_m = \text{Prob.}\{h_{crit}^*(m) > h_{crit}(m)\} \tag{14}$$

where $h_{crit}(m)$ is a fixed value obtained from the data $\mathbf{x}$. Denoting by B the number of bootstrap replications, and defining the indicator variable[16]

$$I_{m,b} = \begin{cases} 1 & \text{if } f_{h_{crit}(m)}(x^*) \text{ has more than } m \text{ modes} \\ 0 & \text{otherwise,} \end{cases}$$

an estimate for the p-value or achieved significance level of the test is given by

$$\widehat{ASL}_m = B^{-1} \sum_{b=1}^{B} I_{m,b}.$$

[16] It was proven by Silverman that the event $h_{crit}^*(m) > h_{crit}(m)$ is equivalent to the event that $\hat{f}_{h_{crit}}(m)(x^*)$ has more than m modes. This result implies that it is not necessary to compute $h_{crit}^*(m)$ for each bootstrap sample; one need only to check the proportion of cases when $f_{h_{crit}}(m)(x^*)$ has more than m modes.

References

Bean, C and Layard, R (1988), 'Why does unemployment persist?', *Discussion Paper No 321*, London School of Economics.

Bentolila, S and Bertola, G (1990), 'Firing costs and labour demand: How bad is eurosclerosis', *Review of Economic Studies*, pages 381–402.

Blanchard, O J and Summers, L H (1987), 'Hysteresis in unemployment', *European Economic Review*, pages 288–95.

Blanchard, B O and Summers, L H (1986), 'Hysteresis and the european unemployment problem', *NBER Macroeconomics Annual*, pages 15–78.

Efron, B and Tibshirani, R J (1993), 'An Introduction to the Bootstrap', Chapman and Hall, *Monographs on Statistics and Applied Probability*, 57, New York.

Gallant, A R (1977), 'Testing for a nonlinear regression specification: a nonregular case', *Journal of the American Statistical Association*, pages 523–30.

Garcia, R and Perron, P (1991), 'An analysis of the real interest rate under regime shifts', Cahier no. 2391, CRDE, Université de Montrèal.

Györfi, L and Härdle, W and Sarda, P and Vieu, P (1989), '*Nonparametric Curve Estimation from Time Series*, Springer Verlag, Berlin.

Hamilton, J D (1994), 'State-space models', *in Handbook of Econometrics, Volume 4* R. Engle and D. Mac Fadden editors. Amsterdam, North Holland.

Hamilton, J D (1989), 'A new approach to the economic analysis of nonstationary time series and the business cycle', *Econometrica*, pages 357–84.

Härdle, W (1990), *Smoothing techniques with implementation in S*, Springer-Verlag, Berlin.

Izenman, A J and Sommer, C J (1988), 'Philatelic mixtures and multimodal densities', *Journal of the American Statistical Association*, pages 941–53.

Karanassou, M and Snower, D J (1993), 'Explaining disparities in unemployment dynamics', *Rivista di Politica Economica*, pages 37–61.

Layard, R and Nickell, S and Jackman, R (1991), *Unemployment, Macroeconomic Performance and the Labour Market*, Oxford University Press, Oxford.

Lindbeck, A and Snower, D J (1988), 'Cooperation, harassment, and involuntary unemployment', *American Economic Review*, pages 167–188.

Lindbeck, A and Snower, D J (1986), 'Wage setting, unemployment and insider–outsider relations', *American Economic Review Proceedings*, pages 235–39.

Manning, A (1990), 'Productivity growth, wage setting and the equilibrium rate of unemployment', *NBER Conference on Unemployment and Wage Determination*, Cambridge MA.

Modigliani, F (1987), 'Reducing unemployment in Europe: The role of capital formation', Technical report, in *The Fight Against Unemployment: Macroeconomic Papers from the Centre for European Policy Studies*, R. Layard and L. Calmfors editors, MIT Press, Cambridge MA.

Perron, P (1989), 'The great crash, the oil price shock, and the unit root hypothesis', *Econometrica*, pages 1361–401.

Phelps, E S (1994), *Structural Slumps - The Modern Equilibrium Theory of Unemployment, Interest, and Assets*, Harvard University Press, Cambridge MA.

Sachs, J (1987), 'High unemployment in europe: diagnosis and policy implications', in *Unemployment in Europe*, Claes Henrie editor, Timbro, Stockholm.

Silverman, B W (1986), *Density estimation for statistics and data analysis*, Chapman and Hall, Monographs on statistics and applied probability No 26, London.

Silverman, B W (1983), 'Some properties of a test for multimodality based on kernel density estimates', *In Probability, Statistics, and Analysis.* JFC Kingman and GEH Reuter editors, Cambridge University Press, pages 248–60.

Silverman, B W (1981), 'Using kernel density estimates to investigate multimodality', *Journal of the Royal Statistical Society, Series B*, pages 97–99.

Summers, L H (1990), *Understanding Unemployment*, The MIT Press, Cambridge, Massachusetts.

Bank of England Working Paper Series

Publication date in italics

1	Real interest parity, dynamic convergence and the European Monetary System *(June 1992)*	Andrew G Haldane Mahmood Pradhan
2	Testing real interest parity in the European Monetary System *(July 1992)*	Andrew G Haldane Mahmood Pradhan
3	Output, productivity and externalities—the case of banking *(August 1992)*	R J Colwell E P Davis
4	Testing for short-termism in the UK stock market *(October 1992)*	David Miles
5	Financial deregulation and household saving *(October 1992)*	Tamim Bayoumi
6	An investigation of the effect of funding on the slope of the yield curve *(January 1993)*	D M Egginton S G Hall
7	A simple model of money, credit and aggregate demand *(April 1993)*	Spencer Dale Andrew G Haldane
8	Bank credit risk *(April 1993)*	E P Davis
9	Divisia indices for money: an appraisal of theory and practice *(April 1993)*	Paul Fisher Suzanne Hudson Mahmood Pradhan
10	The effect of official interest rate changes on market rates since 1987 *(April 1993)*	Spencer Dale
11	Tax specific term structures of interest rates in the UK government bond market *(April 1993)*	Andrew J Derry Mahmood Pradhan
12	Regional trading blocs, mobile capital and exchange rate co-ordination *(April 1993)*	Tamim Bayoumi Gabriel Sterne
13	Temporary cycles or volatile trends? Economic fluctuations in 21 OECD countries *(May 1993)*	Gabriel Sterne Tamim Bayoumi
14	House prices, arrears and possessions: A three equation model for the UK *(June 1993)*	F J Breedon M A S Joyce

15	Tradable and non-tradable prices in the UK and EC: measurement and explanation *(June 1993)*	C L Melliss
16	The statistical distribution of short-term libor rates under two monetary regimes *(September 1993)*	Bahram Pesaran Gary Robinson
17	Interest rate control in a model of monetary policy *(September 1993)*	Spencer Dale Andrew G Haldane
18	Interest rates and the channels of monetary transmission: some sectoral estimates *(September 1993)*	Spencer Dale Andrew G Haldane
19	The effect of futures trading on cash market volatility: evidence from the London stock exchange *(December 1993)*	Gary Robinson
20	M0: causes and consequences *(December 1993)*	F J Breedon P G Fisher
21	An empirical analysis of M4 in the United Kingdom *(December 1993)*	P G Fisher J L Vega
22	A model of building society interest rate setting *(June 1994)*	Joanna Paisley
23	Deriving estimates of inflation expectations from the prices of UK government bonds *(July 1994)*	Mark Deacon Andrew Derry
24	Estimating the term structure of interest rates *(July 1994)*	Mark Deacon Andrew Derry
25	Potential credit exposure on interest rate swaps *(August 1994)*	Ian Bond Gareth Murphy Gary Robinson
26	New currencies in the Former Soviet Union: a recipe for hyperinflation or the path to price stability? *(September 1994)*	C L Melliss M Cornelius
27	Inflation, inflation risks and asset returns *(November 1994)*	Jo Corkish David Miles

28	The construction of RPIY *(February 1995)*	R Beaton P G Fisher
29	Pricing deposit insurance in the United Kingdom *(March 1995)*	David Maude William Perraudin
30	Modelling UK inflation uncertainty: the impact of news and the relationship with inflation *(April 1995)*	M A S Joyce
31	Measuring core inflation *(April 1995)*	Danny T Quah Shaun P Vahey
32	An assessment of the relative importance of real interest rates, inflation and term premia in determining the prices of real and nominal UK bonds *(April 1995)*	David G Barr Bahram Pesaran
33	Granger causality in the presence of structural changes *(May 1995)*	Marco Bianchi
34	How cyclical is the PSBR? *(May 1995)*	Joanna Paisley Chris Salmon
35	Money as an Indicator *(May 1995)*	Mark S Astley Andrew G Haldane
36	Testing for convergence: evidence from nonparametric multimodality tests *(June 1995)*	Marco Bianchi
37	Wage interactions: comparisons or fall-back options *(August 1995)*	Jennifer C Smith
38	The microstructure of the UK gilt market (*September 1995*)	James Proudman
39	Valuation of underwriting agreements for UK rights issues: evidence from the traded option market (*September 1995*)	Francis Breedon Ian Twinn
40	Rules, discretion and the United Kingdom's new monetary framework (*November 1995*)	Andrew G Haldane
41	Optimal commitment in an open economy credibility vs flexibility (*December 1995*)	Sylvester Eijffinger Eric Schaling

42	Bidding and information: Evidence from gilt-edged auctions (*January 1996*)	Francis Breedon Joe Ganley
43	International bank lending to LDCs—an information-based approach (*February 1996*)	Prasanna Gai
44	A comparison of methods for seasonal adjustment of the monetary aggregates *(March 1996)*	Marco Bianchi
45	Base money rules in the United Kingdom (*March 1996*)	Andrew G Haldane Bennett T McCallum Chris Salmon
46	A market for intra-day funds: does it have implications for monetary policy? (*March 1996*)	Spencer Dale Marco Rossi
47	Measurement bias in price indices: an application to the UK's RPI (*March 1996*)	Alastair W F Cunningham
48	The construction of the Bank's new UK commodity price index (*March 1996*)	Andrew Logan Lucy O'Carroll
49	Independence and Accountability *(April 1996)*	Clive B Briault Andrew G Haldane Mervyn A King
50	Unemployment persistence: Does the size of the shock matter? *(June 1996)*	Marco Bianchi Gylfi Zoega