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THE NATURE OF REGIONAL UNEMPLOYMENT IN ITALY

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Abstract: Taking as a starting point the evidence of growing disparities in the 1977-2003 years, the paper investigates the pure hysteresis hypothesis for regional unemployment rates in Italy. Relying both on univariate and panel unit-root tests, we can confidently reject the unit-root hypothesis. The implication of this result is that, however persistent, shocks to regional unemployment will be temporary. We, then, proceed to estimate the NAIRU for each of the 20 Italian regions. Our estimates of the regional NAIRUs turn out to be fairly precise and allow us to draw two interesting conclusions. Firstly, the hypothesis of constant regional NAIRUs between 1977 and 2003 is supported by the data. Secondly, we find that there is a significant degree of heterogeneity among the regional NAIRUs. Finally, we investigate the cyclical behaviour of regional unemployment and find that region-specific demand shocks play a major role.

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The nature of regional unemployment in Italy

1. Introduction

After the low levels of the post-war years, the Italian unemployment rate started to rise significantly from the mid-1970s, reached the 10% threshold in the early 1980s and remained above it until the end of the 1990s. The high-unemployment regions, located in the Mezzogiorno, saw unemployment grow more consistently and are now experiencing to a lesser extent the recent reversion to lower rates recorded at the national level (see Figure 3 in the Appendix). As a result, the last three decades have been characterised by a widening of regional unemployment differentials in Italy, a distinctive feature of the Italian economy.

This pattern does not constitute an anomaly at the EU level. Indeed, the high and highly persistent unemployment rates experienced by many countries and regions in Europe in the same period are commonly cited as evidence in favour of the "hysteresis" hypothesis. While the traditional view of unemployment changes describes them as cyclical deviations from the natural rate or NAIRU, theories which describe the unemployment rate as a hysteretic process suggest that temporary shocks will have permanent effects. Formally, while the first approach implies that the unemployment rate follows a stationary, mean-reverting path, the latter depicts it as a non-stationary, unit root process[1].

Several studies have recently investigated the issue, both on a cross-country and cross-regional basis, but very little work has so far addressed systematically this problem in the context of the Italian regions[2]. The first part of this paper aims at filling this gap in the literature using an array of unit-root tests to assess the stochastic properties of the Italian regional unemployment rates. Though performing several time-series tests as well, we rely primarily on the results of the more powerful panel unit root tests that we also make use of.

[1] At a theoretical level the notion of a non-stationary unemployment rate is clearly problematic since, strictly speaking, a bounded variable cannot be a random walk. However, as León-Ledesma and McAdam (2004) point out, "hysteresis as a unit root should not necessarily be understood as a 'true' description of the data generating process but as local approximation over a sample period" (p. 384). Moreover, as argued by Brunello et al. (2000), the time required for the series to manifest its stationarity may be quite long and "during this interval the unemployment rate is exactly equivalent to a standard unrestricted random walk" (p. 158).

[2] One study that presents evidence pointing to the presence of a unit root in (relative) regional unemployment rates in Italy is that of Brunello et al. (2001). See also Eichengreen (1993) and Brunello et al. (2000).

To preview our results, the panel unit root tests lead us to confidently reject the hysteresis hypothesis in favour of the NAIRU approach. Thus, in the second part of the paper, we move on to the estimation of region-specific NAIRUs and find a significant degree of heterogeneity between them. Moreover, our results suggest that the assumption of a constant NAIRU in the 1977-2003 period fits well the experience of most Italian regions.

Though ultimately mean-reverting, the Italian regions' unemployment rates do display a fairly high degree of persistence, so that they may take a rather long time to recover from temporary deviations from the NAIRU. Taking this into account, we devote the final part of the paper to an analysis of the short-term variation of regional unemployment and again find a high degree of heterogeneity across regions.

The results of our analysis and their implications are finally summarised in the concluding section of the paper.

2. Theoretical background

The seminal contributions of Friedman (1968) and Phelps (1967, 1968) established the notion of the natural rate of unemployment in macroeconomics, characterising it as the (unique) equilibrium rate which unemployment will return to after any temporary deviations[3]. The hypothesis of a stationary, mean-reverting unemployment rate fits well the European and US data for the 1950s and 1960s, but started to be questioned in the 1970s when, particularly in Europe, shocks to unemployment displayed an unusual, by historical standards, degree of persistence. Phelps (1972) firstly suggested that the natural rate of unemployment may not be unique but path-dependent, its value a positive function of the actual unemployment rate, so that it could rise as a consequence of negative shocks leading to prolonged departures from equilibrium[4]. Blanchard and Summers (1986, 1987) argued along the same lines and linked these ideas to the concept of hysteresis to provide an explanation for the high persistence of European unemployment.

Though many studies have since investigated the issue in a variety of ways, the economic meaning of hysteresis, as currently used in the literature, is not unambiguous.

[3] Friedman described the natural rate of unemployment as the unemployment rate that would be "ground out by the Walrasian system of general equilibrium equations" [Friedman (1968, p. 102)].

[4] Thirlwall (1983) shows that the dependence of the NAIRU on the actual unemployment rate is implicit in the estimation framework of the expectations-augmented Phillips curve.

Formally, a variable is subject to hysteresis when it is linearly dependent on a combination of its past values, with coefficients summing up to one. Econometrically, this is equivalent to a unit root process and implies that temporary shocks will have permanent effects on the evolution of the variable under analysis (e.g. the unemployment rate). However, the term hysteresis is also used more “loosely” to identify cases of high persistence, i.e. near unit root processes, in which the variable in question displays mean-reversion, albeit at a very slow speed [Bean (1992)]. The two phenomena have been referred to as, respectively, “pure hysteresis” and “partial hysteresis” [Layard et al. (1991), León-Ledesma and McAdam (2004)].

Unit root tests provide a natural framework to test for “pure hysteresis” and there is now a sizable and growing literature on the topic. The findings of early studies were generally in favour of the unit root hypothesis for the European unemployment, while the evidence for the US was more mixed[5]. However, the reliance of these initial analyses on univariate unit root tests, characterised by low power when the available time series is short and/or the variable under consideration is subject to a high degree of persistence, meant that their results were soon questioned. Critically, given their drawbacks, these tests are particularly unreliable when the unemployment rate is subject to “partial hysteresis”.

Following the general improvements in unit-root testing techniques, two different routes were followed to correct for the low-power problem. The first involves the use of time series tests which allow for the presence of one or more structural breaks in the series[6]. As shown by Perron in his 1989 seminal paper, traditional time series tests are likely to provide evidence in favour of the unit root hypothesis in the presence of a structural break, even though the series under analysis is in fact stationary. Unit root tests with structural breaks allow the researcher to use the entire time series available, as opposed to splitting the sample at the time of the breaks and performing the tests on sub-samples. Thus, they represent a more powerful alternative and have been widely used in the literature on unemployment hysteresis. Examples include Arestis and Mariscal (1999), Papell et al. (2000), Ewing and Wunnava (2001). The second route is that followed by those who rely on the implementation of panel unit root tests, in which case it is the exploitation of cross-sectional information that confers a

[5] See, among others, Nelson and Plosser (1982), Blanchard and Katz (1992), Mitchell (1993), Decressin and Fatás (1995), Røed (1996), Leslie et al. (1995).

[6] Banerjee, Lumsdaine and Stock (1992), Zivot and Andrews (1992) and Perron (1997) develop unit root tests allowing for one break whose location in the series is endogenously determined. Lumsdaine and Papell (1997) extend the test to allow for two breaks.

greater power to the test. Song and Wu (1997, 1998), Johansen (2002) and León-Ledesma (2002) are but a few papers in a fast-growing literature.

Both the univariate unit root tests with breaks and the panel unit root tests have consistently provided little support for the hysteresis hypothesis, either in the US or Europe. This is even more so, however, for the latest advance in unit root testing which combines the advantages of these two testing procedures in developing panel unit root tests with structural breaks. Murrey and Papell (2000), Camarero et al. (2006), Strazich et al. (2001) have used different versions of this new type of tests to investigate unemployment hysteresis in OECD countries and decidedly rejected the unit-root hypothesis.

The most recent evidence, therefore, is in favour of the natural rate or NAIRU approach. The first objective of this paper is that of assessing if this can be confirmed in the case of the Italian regions.

3. Data issues and stylised facts

The unemployment series used in this paper consists of annual data covering the period 1977-2003 and has been reconstructed relying on data collected by ISTAT, the Italian national statistical agency, through its "Quarterly Labour Force Survey" (*Rilevazione Trimestrale sulle Forze di Lavoro*, RTFL).

The design of the RTFL survey and its definition of unemployment have undergone various changes over the years[7] which, since an official ISTAT reconstruction for the entire period is not as yet available, create some complications for empirical work and, in particular, for unit-root testing[8]. In our case, two modifications introduced in 1984 and 1992 create two breaks in the series which must be dealt with in our search for a unit root in regional unemployment rates.

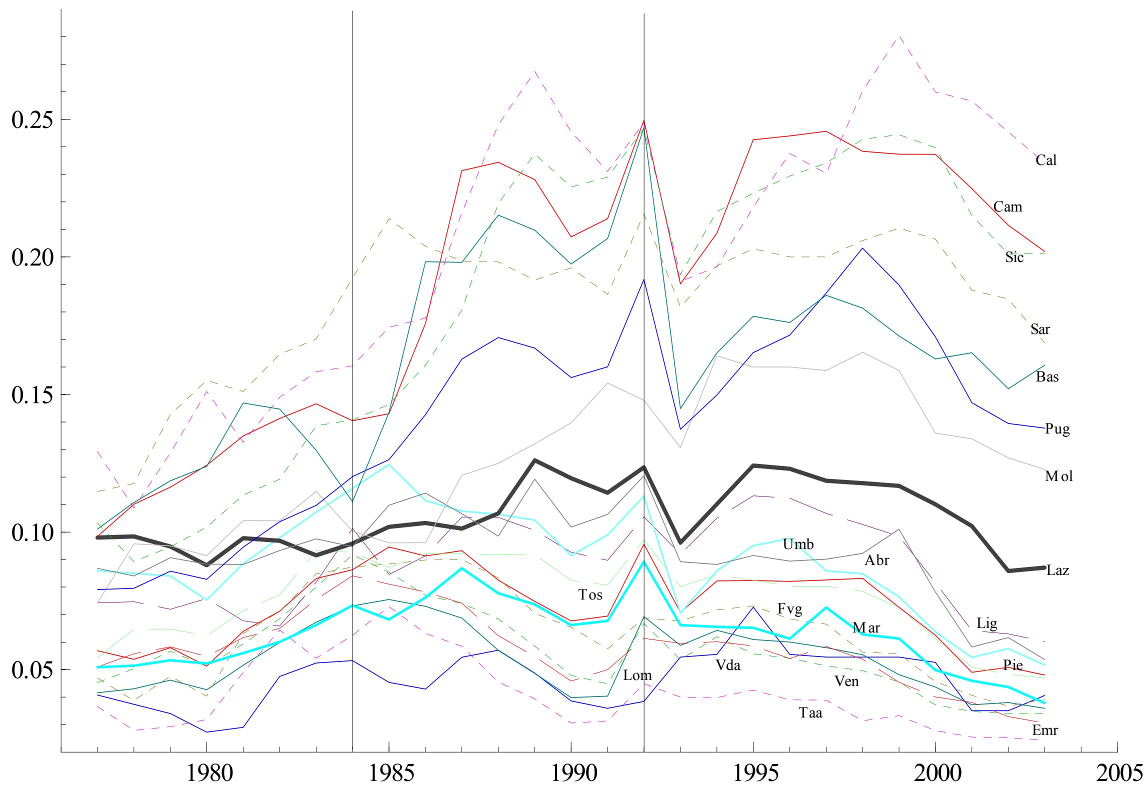
One way of doing so is by carrying out the analysis on the "break-free" 1992-2003 sub-sample. Though feasible, this approach is not very promising as it reduces significantly

[7] The most recent and profound revision occurred in 2004, when, apart from further definition changes, the survey data collection became continuous, i.e. it is now conducted on a weekly basis as opposed to the previous one-week-per-quarter method. As a consequence, the survey is now named "Continuous Labour Force Survey" (*Rilevazione Continua sulle Forze di Lavoro*, RCFL). All the relevant information on the RTFL and the RCFL can be found on the ISTAT website at http://www.istat.it/.

[8] Some authors have relied on homogenous series, characterized by longer times series but usually available for a smaller number of cross-sections [see, for instance, Brunello et al. (2000)].

the already short time-series dimension of our dataset. A viable alternative, which we will primarily rely upon, is that of exploiting the versatility of techniques that allow for the presence of structural breaks in the series, so as to extend the analysis to a longer sample period. Given the short time-span covered by our dataset, the use of multiple-break tests would be problematic, so that we choose to restrict the number of the breaks to one and our search of a unit root in Italian regional unemployment rates to the years 1984-2003[9]. The latter sub-sample allows us to exclude the year 1979 and those immediately following the second oil shock, as well as the recession of the early 1980s, which are likely to present further break problems in the data.

Figure 1 - Regional unemployment rates



[9] Examples of time series unit-root tests allowing for two breaks include those developed by Lumesdaine and Papell (1997) and Lee and Strazich (2003). For a multiple-break panel unit-root test see Carrion-i-Silvestre et al. (2004).

A narrower focus on the most recent years may be interesting in itself since, as illustrated in Figure 1, starting from the late 1990s the Italian regions' unemployment rates show some signs of mean-reversion. The two straight vertical lines in the figure indicate the 1984 and 1992 RTFL breaks. The 1984 modifications of the survey involved primarily an overhaul of the questionnaire, with a significant increase in the number and detail of the questions being asked. Though not immediately apparent from the figure, this resulted on average in an increase of the measured unemployment rate. As for the 1992 revision, the most significant adjustment introduced was the exclusion from the RFTL definition of unemployment of those workers who, though jobless, have not concretely searched for a job in the thirty days preceding the interview. The impact of this methodological change in reducing the measured unemployment rate is clearly visible for most of the regions [10].

Similarly, the higher dispersion of the regional rates at the end of the period considered is apparent and it can be noted that, with the exception of Abruzzo, all the Southern regions' rates display a divergent pattern, both from their values at the beginning of the period and from the remaining regions' rates. Using the coefficient of variation (CV) for a rough check of this visual impression shows that the degree of dispersion of regional unemployment rates has nearly doubled between 1977 and 2003. Furthermore, it increased also within the two sub-groups of the Northern and Southern regions, but much more so among the latter (Table 1)[11].

Table 1 – Coefficient of variation of regional unemployment rates, selected years.

	All regions	Northern regions	Southern regions
1977	0.378	0.337	0.186
2003	0.754	0.369	0.352
Percentage Change	99.47	9.49	89.25

[10] On the general effects of the RTFL 1992 revision see, among others, Casavola and Sestito (1994) and Trivellato (1993).

[11] If one excludes Abruzzo, the degree of dispersion between the Southern regions rises by just about 17.43 per cent in the period. Since the early 1980s, this small region, belonging to the so called "Adriatic Belt", has significantly reduced its gap with the most advanced part of the country, consistently outperforming the other Mezzogiorno economies. In fact, by many economic indexes, Abruzzo is now more similar to the average Northern region than it is to the Southern. For comparability purposes with other studies, we follow the traditional North-South division, while recognising that the inclusion of Abruzzo in the Mezzogiorno sub-group may be questionable.

All of this suggests that devoting attention to the geographical dimension of the problem may be fruitful. Following Blanchard and Katz (1992), researchers have generally done so relying on some type of *relative* regional unemployment rates, that is measuring regional rates with respect to some aggregate (national, EU, etc…) average. Brunello et al. (2001) adopt this approach to analyse the growing unemployment disparities between Italian regions and their degree of persistence. Using a reconstructed series for the 1964-1994 period, they perform several univariate unit-root tests on relative regional unemployment rates, defined as the ratios of the regional to the national rates, and conclude that "not only unemployment differentials exist, but they also diverge in a nonstationary way. In other words, there are no signs of a reversion of the observed diverging tendency towards a common equilibrium" (p. 111). In what follows we re-examine this issue.

4. Unit root tests: a brief overview of the theory

We make use of two univariate unit root tests which allow for the presence of one structural break in the series, occurring at a known date. These tests were developed by Perron (1989, 1990) and are hereafter termed P89 and P90. The first includes a time trend, while the second is appropriate for non-trended data[12]. We choose to perform both of them because in many cases it is not clear which alternative hypothesis between trend- and level-stationarity is more appropriate for the time series we consider. Similarly, we take advantage of the flexibility of these tests in modelling the impact of a structural break on the mean and/or trend of the series and present the results of all the versions of the P89 and P90 tests.

Furthermore, we will rely upon three panel unit root tests developed by Pesaran (2005), Murray and Papell (2000) and Im et al. (2005). The latter two, henceforth respectively referred to as MP and ILT tests, allow for the presence of a structural break in the series[13]. Both the Pesaran (2005) and ILT panel tests are derived from univariate counterparts, so that, for completeness purposes, we will present the results of the latter as well.

[12] The inclusion of a deterministic trend is subject to similar critiques as those relating to the use of unit-root tests (see footnote 1) so that, likewise, similar arguments can be used to justify it. For instance, Papell et al. (2000) observed that "while a nonzero trend for unemployment does not make sense asymptotically, a slowly increasing natural rate could be represented by a trend stationary process in small samples" (p. 309).

[13] The ILT test allows for a maximum of two breaks.

When using unit root tests with breaks, i.e. the P89, P90, MP and ILT tests, we will exogenously impose the 1992 break and perform them on the whole 1984-2003 sample period[14]. However, as it does not consider the possibility of breaks in the series, the implementation of Pesaran's (2005) test is necessarily restricted to the 1993-2003 years.

Perron's tests

In his seminal paper, Perron (1989) showed that, in the presence of a structural break, the traditional univariate tests can lead to the erroneous non-rejection of the null of a unit root when the time series under consideration is trend-stationary. Assuming the break date is known, he proposes unit-root tests which correct for this problem allowing for a one-time change in the intercept and/or the slope of the trend function, under both the null and alternative hypotheses. Nesting the latter, three different models arise:

- A "Crash" or "Additive outlier" (AO) model, which allows for an instantaneous change in the slope and is specified as

$$y_t = \mu + \theta DU_t + \beta t + \delta D\left(TB\right)_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \qquad (1)$$

  where $t = 1,....,T$ indexes time, TB is the break date, $DU = 1$ if $t > TB$ and 0 otherwise, $D\left(TB\right) = 1$ if $t = TB + 1$ and 0 otherwise.

- Two versions of a "Changing growth" or "Innovational outlier" model, where the trend function is assumed to undergo a gradual change. The first model (IO1) allows only for a change in the intercept and can be formalised as follows

$$y_t = \mu + \theta DU_t + \beta t + \delta DT^* + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \qquad (2)$$

[14] This is why, in briefly describing the characteristics of the MP and ILT tests, we do not dwell upon the methods for the endogenous selection of the break date, which both tests include. The reader is referred to the relevant papers.

where $DT^* = t - TB$ if $t > TB$ and 0 otherwise. The second (IO2) includes a change in both the intercept and the trend function:

$$y_t = \mu + \theta DU_t + \beta t + \gamma DT_t + \delta D(TB)_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \quad (3)$$

where $DT = t$ if $t > TB$ and 0 otherwise[15].

In all cases, the null hypothesis of a unit root is rejected if the t-statistic on $\alpha = 1$ is larger (in absolute terms) than the critical values provided by Perron (1989).

In subsequent work, Perron (1990) and Perron and Vogelsang (1992b) adapted the test to the case of non-trended data.

- In its AO version, the P90 test is carried out with a two-step procedure. Firstly, the deterministic part of the series is removed using the estimates from

$$y_t = \mu + \theta DU_t + \tilde{y}_t \quad (4)$$

The test is then performed using the t-statistic for $\alpha = 1$ in the regression

$$\tilde{y}_t = \sum_{i=0}^{k} \delta_i D(TB)_{t-i} + \alpha \tilde{y}_{t-1} + \sum_{i=1}^{k} c_i \Delta \tilde{y}_{t-i} + e_t \quad (5)$$

where $\tilde{y}_t$ are the residuals from (4) and the dummy variables $D(TB)_{t-i}$ are included to ensure that the t-statistic on α is invariant to the value of the truncation lag parameter *k* and has the same asymptotic distribution as in the IO model [Perron and Vogelsang (1992a)].

[15] The test requires the absence of serial correlations in the residuals, thus the inclusion of lagged differences of the data as regressors. As for all the tests considered in this paper, the truncation lag parameter *k* is selected using data-dependent methods.

- The IO model results from excluding the deterministic trend component from equation (1) above. Thus, it is formalised as follows:

$$y_t = \mu + \theta DU_t + \delta D(TB)_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \tag{6}$$

and the null of a unit root is, as usual, tested using the t-statistic on $\alpha = 1$.

Panel unit-root tests

- The test proposed by Pesaran (2005) is an extension of the widely used IPS test [Im et al. (2003)], devised to make it suitable even in the presence of cross-sectional correlation. It is based on the following dynamic linear heterogeneous model for a panel of *N* cross-sectional units and *T* time series observations

$$y_{j,t} = (1-\delta_j)\mu_j + \delta_j y_{j,t-1} + u_{j,t}, \qquad j = 1, \ldots\ldots, N, \qquad t = 1, \ldots\ldots, T \tag{7}$$

It is assumed that the initial values $y_{j,0}$ are given and that the error term, $u_{j,t}$, has the one-factor structure

$$u_{j,t} = \lambda_j \eta_t + \varepsilon_{j,t} \tag{8}$$

where η_t is the unobserved common effect and $\varepsilon_{j,t}$ is a unit-specific idiosyncratic shock. Equations (7) and (8) can be conveniently rewritten as

$$\Delta y_{j,t} = \alpha_j + \beta_j y_{j,t-1} + \lambda_j \eta_t + \varepsilon_{j,t} \tag{9}$$

where $\alpha_j = (1-\delta_j)\mu_j$, $\beta_j = -(1-\delta_j)$ and $\Delta y_{j,t} = y_{j,t} - y_{j,t-1}$. The unit root hypothesis considered is

$$H_0 : \beta_j = 0 \text{ for all } j \tag{10}$$

tested against the possibly heterogenous alternatives

$$H_1 : \beta_j < 0 \,,\; j = 1,2,......,N_1 \,,\; \beta_j = 0 \,, j = N_1 + 1, N_1 + 2,......,N \tag{11}$$

It is further assumed that N_1/N, the fraction of the individual processes that is stationary, is non-zero and tends to the fixed value ϕ such that $0 < \phi \leq 1$ as $N \to \infty$. The assumptions made imply that the composite error, $u_{j,t}$, is serially uncorrelated but this restriction can be relaxed considering stationary error processes of the type

$$u_{j,t} = \sum_{i=1}^{k} \rho_{j,i} u_{j,t-1} + \lambda_j \eta_t + \varepsilon_{j,t} \,.$$

Since the common factor η_t is assumed to be stationary, any non-stationarity in this setting will arise from the autoregressive part of (7), i.e. $\delta_j = 1$ so that $\beta_j = 0$ in (9). To test the null hypothesis (10) in the general case of serially correlated errors, Pesaran (2005) proposes to use the t-ratio of the OLS estimate of b_j $\left(\hat{b}_j\right)$ in the following cross-sectionally augmented Dickey-Fuller (CADF) regression

$$\Delta y_{j,t} = a_j + b_j y_{j,t-1} + c_j \overline{y}_{t-1} + \sum_{i=0}^{k} d_{j,i} \Delta \overline{y}_{t-i} + \sum_{i=1}^{k} \gamma_{j,i} \Delta y_{j,t-i} + e_{j,t} \tag{12}$$

where $\overline{y}_t = N^{-1} \sum_{j=1}^{N} y_{j,t}$, $\Delta \overline{y}_t = N^{-1} \sum_{j=1}^{N} \Delta y_{j,t}$ and $e_{j,t}$ is the regression error. The cross-sectional average $\overline{y}_{t-1}$ is included as a proxy for the unobserved common factor η_t, while the lagged values of $\Delta \overline{y}_t$ and Δy_t correct for autocorrelation. The testing procedure can readily be extended to models containing linear trends.

The panel unit root test is a cross-sectionally augmented version of the IPS test, given by

$$CIPS = N^{-1}\sum_{j=1}^{N} CADF_i \qquad (13)$$

where $CADF_i$ is the cross-sectionally augmented DF statistic for the j-th unit given by the t-ratio of b_j in equation (12). A truncated version of the test is also proposed, where the $CADF_i$ statistics are truncated to avoid undue influences of extreme outcomes when the time series is short (i.e. when T is in the region of 10-20). The truncated versions of the tests are named, respectively, $CADF_i^*$ and $CIPS^*$.

- Building on Perron and Vogelsang (1992a) and Papell (1997), Murray and Papell (2000) construct a panel unit root test for non-trended data which allows for a one-time change in the mean. The test is based on an AO model, the break date and speed of mean-reversion are assumed to be common across the panel units (e.g. regions), while the intercepts, the coefficients on the break dummy and the serial correlation structure are unit-specific. The testing procedure is a panel adaptation of the two-steps method outlined in (4) and (5) above, so that it is based on the following two equations

$$y_{j,t} = \mu_j + \theta DU_{j,t} + \tilde{y}_{j,t} \qquad (14)$$

$$\tilde{y}_{j,t} = \sum_{i=0}^{k} \delta_{j,i} D(TB)_{j,t-i} + \alpha \tilde{y}_{j,t-1} + \sum_{i=1}^{k_j} c_{j,i} \Delta \tilde{y}_{j,t-i} + e_{j,t} \qquad (15)$$

where $j = 1,....,N$ indexes the cross-sections, $t = 1,....,T$, TB is the break date, $DU_{j,t} = 1$ if $t > TB$ and 0 otherwise, $D(TB)_{j,t} = 1$ if $t = TB + 1$ and 0 otherwise and $\tilde{y}_{j,t}$ are the residuals from (14). To allow for contemporaneous correlation, equation (15) is estimated by feasible generalised least squares (SUR) and the unit-root test is then performed using the t-statistic for $\alpha = 1$.

- Im et al. (2005) develop a panel version of the Lagrangian Multiplier (LM) unit-root test proposed by Schmidt and Phillips (1992) and, following Amsler and Lee (1995), extend it to allow for a structural shift in the trend of each individual time series. Amsler and Lee (1995) showed that the asymptotic distribution of the (no-break) LM test does not change when dummy variables are included in the model, implying that "the asymptotic validity of the SP test statistic under the null is not affected by the incorrect placement of the structural break, by the allowance for a break when there is no break, or by no allowance for a break when there is a break" (p. 359). Im et al. (2005) prove that this invariance property carries over to the panel unit-root test under a very mild condition, i.e. that $N/T \to p$, where p is a finite constant, as both $N, T \to \infty$[16].

  We give a brief description of the extended version of the test, in which a structural shift occurs at time TB_j, in the jth time series. In this case the assumed data-generating process (DGP) is

$$\begin{aligned} y_{jt} &= z_{jt} + x_{jt}, \\ z_{jt} &= \gamma_{1j} + \gamma_{2j} t + \delta_j D_{jt}, \\ x_{jt} &= \phi_j x_{i,t-1} + \varepsilon_{jt} \end{aligned} \tag{16}$$

for $j = 1,....,N$, $t = 0,....,T$, where

$$D_{jt} = \begin{cases} 0 & t \le TB_j \\ 1 & t \ge TB_j + 1 \end{cases} \tag{17}$$

The DGP in (16) can be compactly expressed as

$$\Delta y_{jt} = \beta_j y_{j,t-1} - \beta_j \gamma_{1j} + \left[1 - \left(\beta_j + 1\right)\left(t-1\right)\right]\gamma_{2j} + \left(\Delta D_{jt} - \beta_j D_{j,t-1}\right)\delta_j + \varepsilon_{jt} \tag{18}$$

where $\beta_j = -\left(1 - \phi_j\right)$ and $\Delta D_{jt} = D_{jt} - D_{j,t-1}$, i.e.

[16] The authors do not consider structural changes which affect the slopes of the time trend. In such a case the invariance property of the LM test statistic does not hold [Strazicich et al. (2001)].

$$\Delta D_{jt} = \begin{cases} 1 & t = TB_j + 1 \\ 0 & otherwise \end{cases} \tag{19}$$

The null hypothesis of a unit root is

$$H_0 : \beta_j = 0 \text{ for all } j \tag{20}$$

which is tested against the alternative

$$H_1 : \beta_j < 0 \text{ for some } j \tag{21}$$

Assuming that the error terms ε_{jt} are independent normal variables with zero mean and variance σ_j^2, Im et al. (2005) show that the LM statistic derived from the ensuing pooled-likelihood function is just equal to the sum of the individual LM statistics for each time series. Following Amsler and Lee (1995), the LM statistic for the *j*th time series, $t_{LM,jT}^B$, is equivalent to a t-statistic on $\beta_j = 0$ in

$$\Delta y_{jt} = \gamma_{2j} + \delta_j \Delta D_{jt} + \beta_j \tilde{S}_{j,t-1} + error \tag{22}$$

where

$$\tilde{S}_{j,t-1} = y_{j,t-1} - \tilde{\gamma}_{2j}\left(t-1\right) - \tilde{\delta}_j D_{j,t-1} \tag{23}$$

and $\tilde{\gamma}_{2j}$ and $\tilde{\delta}_j$ are OLS estimates of γ_{2j} and δ_j in the following restricted regression

$$\Delta y_{jt} = \gamma_{2j} + \delta_j \Delta D_{jt} + \varepsilon_{jt} \tag{24}$$

The distributions of $t_{LM,jT}^B$ are asymptotically independent from the location of the shift point $\lambda_j = \dfrac{TB_j}{T}$, but this property does not hold for the panel unit root statistic. Specifically, the expected values of the mean and variance of $t_{LM,jT}^B$ under the null hypothesis, which are needed for the construction of the panel LM test, are a function of λ_j. However, Im et al. (2005) show that, unless N/T diverges as $N,T \to \infty$, it is possible to use the same expected values for the means and variances as calculated for the "no-shift" case, denoted $E\left(\tau_{LM,T}\right)$ and $V\left(\tau_{LM,T}\right)$, regardless of the presence of a structural shift in the series. Thus, assuming this condition holds, they suggest the following panel unit-root test statistic

$$\Gamma_{LM}^{B} = \frac{\sqrt{N}\left[\overline{t}_{LM,NT}^{B} - E\left(\tau_{LM,T}\right)\right]}{\sqrt{V\left(\tau_{LM,T}\right)}} \Rightarrow N\left(0,1\right) \tag{25}$$

where

$$\overline{t}_{LM,NT}^{B} = \frac{1}{N}\sum_{j=1}^{N} t_{LM,jT}^{B} \tag{26}$$

Finally, the test assumes cross-sectional independence but serial correlation in the errors ε_{jt} of equation (18) can be corrected for via the introduction of the lagged differences $\Delta\tilde{S}_{j,t-i}$, i.e.

$$\Delta y_{jt} = intercept + \delta_j \Delta D_{jt} + \beta_j \tilde{S}_{j,t-1} + \sum_{i=1}^{k_i} \rho_{ji} \Delta\tilde{S}_{j,t-i} + error \tag{27}$$

As before, the LM statistic for the *j*th time series is given by the t-statistic on $\beta_j = 0$, which is denoted $t_{LM,jT}^{B}\left(k_i\right)$. Assuming N/T does not diverge as $N,T \to \infty$, the corresponding panel unit-root LM statistic is

$$\Gamma_{LM}^{B}\left(k\right) = \frac{\sqrt{N}\left\{\overline{t}_{LM,NT}^{B}\left(k\right) - \frac{1}{N}\sum_{j=1}^{N} E\left[\tau_{LM,T}\left(k_i\right)\right]\right\}}{\sqrt{\frac{1}{N}\sum_{j=1}^{N} V\left[\tau_{LM,T}\left(k_i\right)\right]}} \Rightarrow N\left(0,1\right) \tag{28}$$

where

$$\bar{t}^{B}_{LM,NT}\left(k\right)=\frac{1}{N}\sum_{j=1}^{N}t^{B}_{LM,jT}\left(k_i\right) \tag{29}$$

The values of $E\left(\tau_{LM,T}\right)$ and $V\left(\tau_{LM,T}\right)$ for various combinations of T of k are computed by Im et al. (2005) via stochastic simulations and reported in their Table 1.

Before proceeding to performing the tests on the Italian regional data, we briefly discuss two issues which relate to the use of panel unit root tests in general and, thus, could have some bearing on the results of our analysis. The first is the assumption of a homogenous root for all the series in the panel that is often imposed under the null, as it significantly increases the power of the test. Pesaran and Smith (1995) and Pesaran et al (1996) demonstrate the inconsistency of pooled estimators in dynamic heterogeneous panel models and show that, if the autoregressive roots differ across units, pooled estimation will provide an upward-biased estimate. Thus, tests which rely on the homogeneity assumption, such as the MP test we make use of, can potentially be biased in favour of the non-rejection of the null of a unit root. Consequently, the results from these tests must be treated with some care.

The second issue is that many panel unit root tests, such as the ILT test we use, assume the absence of any cross-sectional dependence between the series in the panel. This is generally recognised as a strong assumption and when it is wrongly imposed a size distortion of the test ensues which lowers its power in rejecting the null of a unit root [see O'Connel (1998), Jönsson (2005)]. Cross-sectionally demeaning the series can partly deal with the problem, removing some of the correlation[17]. We resort to this method when performing the ILT test.

[17] The demeaning procedure will entirely wipe out cross-sectional dependence only if the pair-wise cross-section covariances of the error terms are homogenous across the panel units. This will not be true in general, so that a number of new tests have recently been proposed to correct for this problem, such as Chang's (2002), Bai and Ng's (2004) and Pesaran's (2005). Among them, and potentially suitable in our case, are also Phillips and Sul's (2003) and Moon and Perron's (2004). These two papers develop similar approaches based on the modelling of cross-sectional correlation as dependent on a number of unobserved common factors. The authors suggest estimating the latter in order to "de-factor" the series and eliminate any cross-sectional dependence, before proceeding to the panel unit-root testing. Their procedures, however, are valid only asymptotically so that, given the uncertainty as to their small sample performance and the short time-series of our panel, we choose not to rely on them.

5. Unit root tests: results

Given the low-power problems which afflict univariate tests, we place primary weight on the panel unit root tests. Thus, here we focus on the general conclusions which can be drawn from the implementation of the time series tests, while reporting the complete set of results in the Appendix (Tables A1 to A7).

Table 2 – Univariate Unit root tests on the 20 Italian regions, number of rejections of the null hypothesis at the 1%, 5% and 10% significance levels.

		CADF*		P89			P90		ILT
		Intercept	Intercept & trend	AO	IO1	IO2	AO	IO	
Absolute	1%	3	0	0	1	0	2	0	3
Unemployment	5%	0	2	0	0	1	1	0	3
rates	10%	0	0	1	1	0	1	1	1
Average root		0.761	0.618	0.776	0.273	0.550	0.661	0.670	0.519
(Half life)		(2.538)	(1.440)	(2.733)	(0.534)	(1.159)	(1.674)	(1.731)	(1.057)
Relative	1%	1	0	4	8	4	0	1	1
Unemployment	5%	2	1	1	0	0	4	2	4
rates	10%	1	3	1	2	0	4	1	5
Average root		0.594	0.137	0.189	0.112	0.149	0.583	0.641	0.450
(Half life)		(1.331)	(0.349)	(0.416)	(0.317)	(0.364)	(1.285)	(1.559)	(0.868)

Notes:
The CADF* tests are performed on the 1993-2003 period, while the P89, P90 and ILT tests consider the 1984-2003 time span, with an exogenously imposed break in 1992;
The half life is expressed in years and computed as $-\ln(2)/\ln(\xi)$, where ξ is the estimated autoregressive root.

Table 2 considers the four univariate tests we rely upon in their different versions and, for each one of them, reports the number of rejections of the null of a unit root at three different significance levels. With the possible exception of the ILT test, which rejects the null for 7 out of the 20 Italian regions (one of them only at the 10% level of significance), the results for the absolute unemployment rates are decidedly in favour of the hysteresis hypothesis. However, the estimated roots are generally much smaller than one, indicating that the non-rejection of the null may well depend largely on the low power of the tests.

When we turn our attention to the relative unemployment rates the results are less clear-cut. The total number of rejections increases considerably (from 21 to 50) and both the P89-IO1 and the ILT tests provide evidence of stationarity in 50 per cent of the cases. Moreover, the estimated roots are consistently smaller, sometimes significantly so. Using as an example the most striking case, the P89-AO test gives an average estimated root of 0.776 for the absolute unemployment rates, while the corresponding value for the relative unemployment rates is only 0.189. Taking these results at face value, and abstracting for a moment from the possible presence of a unit root, the calculated half lives tell us that the average region's absolute unemployment rate will take nearly three years to absorb half of the impact of a shock, while 50 per cent of the reversion to its equilibrium value with respect to the national unemployment rate will be completed in less than two quarters. In other words, region-specific shocks seem to be less persistent than common, national shocks[18].

It may, thus, be interesting to investigate to what extent the shocks affecting regional unemployment rates have a national character, as one could expect *national* economic policies to be largely effective in addressing the short-term volatility of *regional* unemployment rates if the latter share a common cycle. This issue will be taken up in the last section of the paper.

Before doing so, however, we need to gather stronger evidence against the unit root hypothesis. An analysis of the cyclical behaviour of unemployment, in fact, is only legitimate if we can convincingly exclude "pure hysteresis". The results in Table 1 do not allow us to do so, but confirm the concerns expressed as regards the reliability of univariate tests in our case. The 1992 break imposes a constraint on the CADF* regressions, which necessarily use only the 11 observations between 1993 and 2003. With such a short time-series the small number of rejections is not a surprise. The time-span extension granted by the use of tests which allow for a break in the series reduces to some extent the low-power problem, but this is still apparent when one considers the size of the estimated roots. We, thus, take a further step in following the course suggested in the literature to deal with these issues and move on to performing panel unit-root tests and panel unit-root tests with structural breaks.

[18] On this point, see Decressin and Fatás (1995).

Table 3 – Panel Data unit-root tests on regional unemployment rates

Region	CIPS*				MP		ILT	
	Intercept		**Intercept & trend**					
	T-ratio	Root (half life)	T-ratio	Root (half life)	T-ratio	Root (half life)	T-ratio	Root (half life)
				Absolute unemployment rates				
All regions	-1.701	0.761 (2.533)	-1.849	0.618 (1.440)	-22.762^	0.711 (2.033)	-3.591^	0.519 (1.057)
Northern regions	-2.728*	0.631 (1.507)	-2.156	0.509 (1.027)	-8.193	0.740 (2.306)	-1.634	0.581 (1.279)
Southern regions	-0.161	0.955 (14.927)	-1.389	0.781 (2.806)	-6.728	0.557 (1.186)	-3.664^	0.425 (0.811)
				Relative unemployment rates				
All regions	-1.873	0.594 (1.329)	-2.513	0.137 (0.349)	-20.463^	0.287 (0.556)	-4.649^	0.450 (0.868)
Northern regions	-1.935	0.589 (1.308)	-2.314	0.125 (0.333)	-10.549*	0.341 (0.644)	-4.178^	0.406 (0.769)
Southern regions	-1.780	0.601 (1.361)	-2.812	0.156 (0.373)	-9.070^	0.584 (1.289)	-2.232*	0.517 (1.049)

Notes:
The CIPS* tests are performed on the 1993-2003 period, while the MP and ILT tests consider the 1984-2003 time span, with an exogenously imposed break in 1992;
^ and * indicate, respectively, rejection of the null of unit root at the 1% and 5% level of significance;
In each case, the reported roots are simple averages of the relevant regional estimates;
The MP test on "All regions" for the absolute unemployment rates excludes the regions Valle d'Aosta, Umbria, Campania and Calabria;
The MP test on "All regions" for the relative unemployment rates excludes the regions Valle d'Aosta, Lazio, Campania, Puglia and Basilicata. With the inclusion of Valle d'Aosta the absolute value of the t-statistic increases to 24.010.

Table 3 reports the results of the three panel unit-root tests which we make use of, i.e. the CIPS*, MP and ILT tests. As well as considering all the regions together, we also run the tests on the two sub-samples of the Northern and Southern regions. However, because of the insufficient time dimension, the MP test could not be performed on the entire sample of 20 regions[19]. We, thus, selected a sub-sample excluding the small region of Valle d'Aosta and

[19] SUR estimation requires the number of equations to be strictly smaller than the number of time points available for estimation.

those regions for which the unit root hypothesis was rejected by the correspondent univariate tests, i.e. the P90-AO tests (see Tables A2 and A4 in the Appendix). Since the null hypothesis being tested is that of a unit root for all regions in the sample, this seems a convenient way of solving the problem as it makes the results of the MP test more meaningful.

The CIPS* confirms the evidence gathered using univariate tests, rejecting the unit root hypothesis only in one case, i.e. that of the Northern regions' absolute unemployment rates. Given the short time-series used, this result is not unexpected and reinforces our arguments for the implementation of panel unit root tests that allow for a structural break, which are further borne out by the MP and ILT estimates[20].

The MP test strongly rejects the null of a unit root both for the absolute and relative rates of unemployment. However, when the sample is split according to the North-South distinction, the null cannot be rejected in the case of the absolute unemployment rates. Given the sensitivity of this test to the time dimension of the panel, this result may be due to the larger number of lags included in the latter estimations. As for the ILT test, it consistently rejects the unit root hypothesis in all of the cases except that of the Northern regions' absolute unemployment rates[21].

Finally, even breaking down the analysis according to the North-South distinction, the estimated roots and half-lives reflect the pattern already noticed for the univariate tests, with the absolute unemployment rates displaying a higher degree of persistence than the relative rates[22].

To sum up, the results from the panel unit root tests lead us to reject the "pure hysteresis" hypothesis in the case of the Italian regions in favour of the NAIRU approach. In turn, contrary to the non-stationary divergence process depicted by Brunello et al. (2001), this suggests that the regional unemployment differentials observed in the 1984-2003 period reflect mainly differences in mean rates and, thus, structural components.

We now turn to the assessment of these differences via the estimation of the region-specific NAIRUs.

[20] In assessing the Monte Carlo evidence on the small sample performance of various versions of his test in the no-trend case with serially uncorrelated errors, Pesaran (2005) notes that none "exhibit much power when $T = 10$, irrespective of the size of *N*. Only when *T* is increased to 20 and beyond one can begin to see the benefit of increasing *N* on the power of the tests" (p. 22). This remark remains valid even when serial correlation is corrected for and/or the model is modified with the introduction of a linear trend.

[21] The probability value is in this case 10.3%.

[22] The CIPS* and ILT roots for the "All regions" case in Table 2 are the same as in Table 1, as they are again calculated as simple averages of the individual CADF* and ILT estimates.

6. NAIRU: Theory and estimation

McAdam and McMorrow (2003) identify two broad modelling approaches which have been followed in the literature to measure the NAIRU. The first defines the NAIRU as that particular unemployment rate at which a stable Phillips-curve-type relationship exists between the deviation of unemployment from the NAIRU and unexpected inflation. Within this framework there is a further distinction between the single-equation inflation approach and the multiple-equation wage-price model. The latter involves the modelling of the labour market, wage- and price-setting behaviour and defines the NAIRU as the unemployment rate which characterises equilibrium with fully-realised expectations [Layard et al. (1991)]. An example of the application of such a methodology in the case of Italy is provided by Brunello et al. (2000), who use it to measure the NAIRU for the Northern and Southern macro-regions for the period 1954-1994.

Though providing a robust theoretical framework, the use of these structural models to estimate the NAIRU is problematic in many respects, e.g. the choice and specification of the appropriate theoretical model, statistical identification and data availability [see Richardson et al. (2000)]. While all of these issues represent a concern, in our case the lack of data availability precludes the utilisation of this approach to achieve our primary objective in this section, i.e. bringing the analysis of the NAIRU to the regional level in Italy.

We, thus, opt for the second, alternative strategy of measuring the NAIRU by relying solely on the univariate properties of unemployment. This is based on the assumption that over time the unemployment rate reverts to its mean or natural rate, so that a necessary preliminary step for the implementation of this approach is the ruling out of hysteresis in unemployment. While the latter problem has been dealt with in the previous section, before proceeding with the statistical estimation of the NAIRU we need to discuss a further theoretical issue relating to its stability over time.

Three different methodologies can be followed to address this: the first, corresponding to the traditional view, assumes that the NAIRU is constant; the second relates to the case in which unemployment is a stationary process around an occasionally changing mean, so that the NAIRU is subject to sudden permanent changes, possibly following particularly large shocks; the third assumes the NAIRU is smoothly changing over time and provides a visual illustration of its time-varying nature by decomposing the actual unemployment rate in a trend-cycle fashion, using filtering techniques such as the Hodrick-Prescott or Kalman filters.

While not without merits, the latter approach is subject to many critiques, particularly because the displayed time-evolution of the NAIRU will depend on the degree of smoothness chosen for the filtering technique. The possibility of an infrequently changing NAIRU appears more appealing and a few recent papers have applied the likes of multiple-break or Markov-switching techniques to tackle it[23]. However, as already mentioned, the characteristics of our data-set would make the use of these techniques very problematic in our case.

We, thus, opt for the first strategy and start by estimating the Italian regions' NAIRUs assuming they are constant in the period under analysis. Subsequently, we formally test the accuracy of this assumption and rely on recursive OLS regressions to provide some evidence as regards the time-evolution of the regional NAIRUs in the last decade.

The univariate approach

Staiger et al. (1997) set up the univariate approach to the NAIRU estimation starting with the following autoregressive model

$$U_t - \bar{U}_t = \beta(L)\left(U_{t-1} - \bar{U}_{t-1}\right) + \varepsilon_t \tag{30}$$

where $\bar{U}_t$ is the NAIRU and $\beta(L)$ is a lag polynomial, introduced to account for persistence effects, also referred to as "speed-limit" effects. If the NAIRU is constant, equation (30) can be expressed as

$$U_t = \mu + \beta(L)U_{t-1} + \varepsilon_t \tag{31}$$

and the NAIRU is thus equal to

$$\bar{U}_t = \frac{\mu}{1-\beta(1)} \tag{32}$$

[23] See, for instance, León-Ledesma and McAdam (2004) and Camarero et al. (2006).

where $\beta(1)=\sum_0^k \beta_i$ and k is the order of the lag polynomial $\beta(L)$.

Using the entire 1977-2003 sample period, we follow this approach and estimate the NAIRU by SUR methods, to correct for the likely presence of cross-sectional correlation[24]. Heterogeneous intercepts and slopes are allowed for and the lag selection is performed with a general-to-simple procedure, with the maximum number of lags set to 3 because of the short time-series available.

In our case, the measurement of the regional NAIRUs is somewhat complicated by the presence of the 1984 and 1992 definition changes. We deal with these breaks using two intercept dummies and use the values of the estimated coefficients on these to compute the NAIRUs according to the post-1992 definition of unemployment. Formally, we regress the following version of (31)

$$U_t = \mu + \beta(L)U_{t-1} + \theta_{84} + \theta_{92} + \varepsilon_t \qquad (31')$$

where θ_{84} and θ_{92} are the two intercept dummies. Thus, the estimated NAIRU is

$$\bar{U}_t = \frac{\mu + \theta_{84} + \theta_{92}}{1-\beta(1)} \qquad (32').$$

Next, we compute the delta-method standard errors and the corresponding confidence interval (CI) for each regional NAIRU as formalised in (32'). To do so, we apply the procedure suggested by Papke and Wooldridge (2005). Briefly stated, in our case this involves the following steps.

(1) First, defining the parameter of interest given in (32') as $\lambda = r(\beta)$, find the gradient $g(\beta)$ of $r(\beta)$, which involves computing the p partial derivatives $\partial r(\beta)/\partial \beta_h$ for $h = 1,....,p$.

(2) Using the vector of parameter estimates $\hat{\beta}$ from (31'), evaluate $g(\beta)$ at $\hat{\beta}$ to obtain $\hat{g} \equiv (\hat{g}_1, \hat{g}_2, ...\hat{g}_p)$.

[24] Single-equation results are found to be slightly different in size and much less precise than the SUR estimates, thus confirming the presence of significant cross-sectional correlation. The results are not reported here.

(3) Choose a non-zero element of $\widehat{g}$, for example $\widehat{g}_j$. For each observation of the regressors $\tilde{x}_h$'s, define transformed regressors $\tilde{x}_h \equiv \left[x_h - \left(\widehat{g}_h / \widehat{g}_j \right) x_j \right]$ for $h \neq j$, and $\tilde{x}_j \equiv x_j / \widehat{g}_j$.

(4) Substitute the transformed regressors $\tilde{x}_h$, $h = 1, ..., p$ and re-estimate equation (31'). The estimated coefficient on $\tilde{x}_j$ is $\widehat{\lambda}$, i.e. the estimate of the NAIRU given in (32'), while the associated standard error is the delta-method standard error.

We choose the estimated constant from (31') as the non-zero element $\widehat{g}_j$ to be used in the transformation of the regressors. As a result, the intercepts from the re-estimation of (31') with the transformed regressors will provide us with the values of (32'), i.e. the region-specific NAIRUs. This, in turn, allows us to analyse other NAIRU-related issues by conducting direct hypothesis-testing on these intercepts.

Estimation results

The regional NAIRU estimates and the associated confidence intervals are reported in Table 4 below. The difficulty in obtaining precise estimates of the NAIRU is a fairly well-established fact in the literature [see Staiger et al (1997)]. In our case the 95% CI width is on average about 1.46 percentage points, while the comparable measure from Brunello et al. (2000) is about 2%. It can also be noted that the precision of the estimates is higher for the northern regions (the CI width is on average 1.14%) than for the southern regions (1.94%).

We formally assess the constancy-assumption using Hansen's (1992) instability test and this indicates that the constant-NAIRU hypothesis cannot be rejected at conventional significance levels. Moreover, the RESET test rejects the null hypothesis of a linear functional form only in 3 out of 20 cases. This provides supportive evidence for the reliability of the results.

Table 4 – Regional NAIRU estimates

Region	Root	Half life	NAIRU (CI)	Hansen p-value	Reset F (p-value)
Piemonte	0.583	1.285	6.16 (5.51 – 6.82)	0.086	1.732 (0.202)
Valle d'Aosta	0.440	0.844	5.16 (4.68 – 5.63)	0.150	0.666 (0.424)
Lombardia	0.634	1.521	4.42 (3.92 – 4.93)	0.079	0.238 (0.631)
Trentino Alto Adige	0.236	0.480	3.43 (3.03 – 3.84)	0.063	0.137 (0.715)
Veneto	0.689	1.861	3.87 (3.39 – 4.35)	0.073	0.966 (0.337)
Friuli Venezia Giulia	0.524	1.073	5.80 (5.42 – 6.19)	0.069	0.143 (0.709)
Liguria	0.844	4.087	6.69 (5.63 – 7.75)	0.105	0.377 (0.546)
Emilia Romagna	0.779	2.775	3.66 (3.26 – 4.05)	0.103	0.069 (0.795)
Toscana	0.751	2.421	5.39 (4.82 – 5.97)	0.067	2.407 (0.136)
Umbria	0.510	1.029	6.77 (6.02 – 7.53)	0.092	0.207 (0.654)
Marche	0.570	1.233	5.05 (4.47 – 5.62)	0.087	6.142* (0.022)
Lazio	0.508	1.023	10.42 (9.83 – 11.00)	0.095	0.035 (0.852)
Abruzzo	0.425	0.810	7.58 (6.90 – 8.26)	0.113	11.501^ (0.003)
Molise	0.745	2.355	14.05 (13.30 – 14.81)	0.100	0.488 (0.492)
Campania	0.466	0.908	22.07 (20.95 – 23.19)	0.053	1.368 (0.255)
Puglia	0.542	1.132	15.63 (14.64 – 16.62)	0.080	1.829 (0.191)
Basilicata	0.180	0.404	16.48 (15.40 – 17.56)	0.075	0.235 (0.633)
Calabria	0.523	1.069	23.55 (22.35 – 24.74)	0.080	0.069 (0.795)
Sicilia	0.750	2.409	20.77 (19.63 – 21.92)	0.066	2.647 (0.119)
Sardegna	0.379	0.714	19.05 (18.25 – 19.84)	0.069	4.675* (0.042)
All regions	0.554	1.472	10.30		
Northern regions	0.589	1.636	5.57		
Southern regions	0.501	1.225	17.40		

Notes:
CI is the NAIRU confidence interval, computed using delta method standard errors;
The "All regions", "Northern regions" and "South regions" estimates are computed as simple averages of the relevant regional values.
^ and * indicate, respectively, rejection at the 1% and 5% level of significance.

As an additional check and to give a visual illustration of the evolution of the regional NAIRUs over time, we investigate the stability issue further via recursive OLS estimations and, for every region, plot the results in Figure 3A in the Appendix. Because of the uncertainty related to the initial estimates and the presence of the two breaks, we choose a fairly long window of 16 years and focus on the last 10 years of our sample, so that the recursive regression plots display the evolution of the regional NAIRUs between 1994 and 2003. Though covering a longer time-span would be desirable, arguably it is the assessment of the NAIRUs in the last decade that conveys the most useful information in terms of current economic policy implications.

For most of the regions, the NAIRU appears fairly stable over the period 1994-2003. A clear exception is represented by Abruzzo, while Liguria is another uncertain case. To check formally for the possible presence of significant breaks, we perform 1-step and break-point Chow tests and find that these cannot reject the null hypothesis of parameter stability for any of the regions except Abruzzo[25].

Overall, the evidence gathered leads us to conclude that the regional NAIRUs have not changed significantly in the period under consideration and, thus, that the constant-NAIRU hypothesis is a reasonable assumption in our case.

Turning to a closer discussion of the results reported in Table 4, it can be noted that there is considerable heterogeneity between the estimated regional NAIRUs. This is in line with the results of the unit-root tests. As mentioned, the ascertained stationarity of unemployment rates suggests that the persistent differentials observed between the Italian regions over long periods of time depend on structural factors, i.e. reflect underlying different region-specific NAIRUs. We test formally whether our estimation results support this hypothesis.

Taking the versions of (31') with transformed regressors obtained from the Papke and Wooldridge's (2005) procedure, we pool the regional equations and estimate them by SUR allowing for unit specific NAIRUs and then imposing the cross-equation restriction of a homogenous intercept. We do this for the whole sample of 20 regions as well as for the sub-samples of the Northern and Southern regions and then compute the appropriate likelihood ratio (LR) test statistics, as well as multivariate versions of the Akaike Information Criterion

[25] The results of the Chow tests for all the regional recursive regressions are not reported here, but they provide significant evidence of a break in 2001 in Abruzzo's unemployment rate. Indeed, in that year the region's unemployment rate fell by about 2 percentage points, from 7.8 to 5.8 per cent. However, in 2002 it went back up to 6.1 per cent, before decreasing again by 0.8 percentage points in 2003. Given this evidence, it is yet not possible to determine whether the year 2001 can be considered as just an outlier or, rather, it is a structural break signalling a permanent downward shift of the NAIRU.

(*AIC*) and the Schwartz Bayesian Criterion (*SBC*) to compare the constrained and unconstrained regressions[26].

As can be seen from the results reported in Table 5, in each of the three cases considered, the LR test strongly rejects the null of cross-regional homogeneous NAIRUs, while the AIC and the SBC indicate that the unconstrained model provides the best fit of the data[27].

Table 5 – Hypothesis testing of cross-regional NAIRU homogeneity

Region	**LR test**	**AIC**		**SBC**	
		Unconstrained	*Constrained*	*Unconstrained*	*Constrained*
All regions	354.019^	-5024.384	-4595.834	-4922.190	-4493.640
Northern regions	128.730^	-2989.097	-2833.265	-2925.509	-2769.678
Southern regions	112.751^	-1724.778	-1589.476	-1684.723	-1549.422

Notes:
^ indicates rejection at the 1% level of significance.

Based on this, we conclude that regional NAIRUs are indeed significantly different from each other, even within the two Northern and Southern macro-regions. This suggests that studies analysing the Italian NAIRU should be conducted at the regional level, as any type of aggregation, either national of sub-national, is likely to be misleading.

This is why we compute the values reported at the bottom of Table 4 as simple averages of the relevant regional values. That is, the estimate of 10.3 per cent for the "All regions" case, for instance, does *not* measure Italy's aggregate NAIRU in the period but, rather, gives an indication of the average Italian region's NAIRU. We may also observe that, despite the significant heterogeneity found within the two sub-groups, there is a clear divide between the average Northern and Southern regions, with the latter featuring a NAIRU more than three times higher than the former. Taking the national average of about 10 per cent as a

[26] The likelihood ratio statistic is based on asymptotic theory, so that the AIC and SBC are usually also relied upon when the sample available is relatively small.

[27] The exclusions of Abruzzo and Lazio from, respectively, the Southern and Northern regions sub-samples do not change the outcome.

threshold, one notes that all of the Northern regions except Lazio are below it, while all of the Southern regions except Abruzzo are above.

Finally, apart from a handful of cases, the size of the estimated roots is fairly homogenous across regions, so that the average value of about 0.55 gives a meaningful indication of the degree of persistence characterising regional unemployment in Italy. This holds even when splitting the sample according to the North-South distinction and, more generally, is in line with the results of the unit root tests (see Table 3).

In conclusion, our investigation of the Italian regions' NAIRUs brings support to the idea that the observed unemployment disparities reflect underlining structural differences between the regional NAIRUs, which in turn appear fairly stable in the last three decades or so. In terms of economic policy indications, this suggests that policies aimed at combating persistently high regional unemployment and regional unemployment disparities should be largely region-specific in character. Neglecting regional differences, national policies, i.e. policies which are homogenous across regions, are likely to be unsuccessful in achieving either target.

7. Cyclicality, common and region-specific shocks

The absence of a unit-root in regional unemployment rates implies that any divergence from the NAIRU will be temporary, with unemployment returning to its equilibrium rate in the medium- to long-term. Nonetheless, the short-term deviations of regional unemployment rates can be significant and, as noted, rather persistent, so that their effects on regional economies are not trivial. Thus, together with the primary objective of reducing long-term regional unemployment disparities via policies aimed at decreasing the NAIRU in high-unemployment regions, moderating the short-term volatility of regional unemployment rates may be rightly considered as an additional valuable policy target. To this end, an accurate analysis of the cyclical pattern of regional unemployment is essential.

Following the original work of Thirlwall (1966) and Brechling (1967), several papers over the years have studied the cyclical behaviour of regional unemployment rates examining their relationship with the national rate[28]. The procedure involves a simple regression of the

[28] Recent examples include Gray (2004), Martin (1997) and Payne et al. (1999).

regional rate on the national one and can be performed with the variables in absolute or logarithmic form, either in levels or first differences. In such a framework, the coefficient on the national unemployment rate is usually held to provide a measure of the regional sensitivity to the national cycle, with values higher (lower) than one characterising sensitive (non-sensitive) regions. In addition, the regression R^2 indicates how much of the variation in the regional unemployment rate is accounted for by aggregate unemployment changes, i.e. "national" shocks[29].

The technique has been criticised in various respects, mainly related to the lack of an explicit theoretical foundation[30]. Recently, however, Dixon and Shepherd (2001) have also argued against its use as a method of data description, suggesting, among other things, that the Engle and Kozicki's (1993) (hereafter EK) "common-feature" test should be preferred instead, as this approach provides a more rigorous assessment of the common-cycle hypothesis than the Brechling-Thirlwall (hereafter BT) framework[31].

The EK technique can be used to assess whether some feature characterising each of several stationary time series in a dataset is common to them[32]. Examples of such features include heteroskedasticity, trends, seasonality, ARCH and serial correlation, which we will be focusing on since, as shown by Vahid and Engle (1993), the presence of serial correlation in a stationary series implies the existence of a cyclical component.

Briefly stated, the estimation methodology consists of two steps. Firstly, tests are carried out to establish whether a certain feature z_t is present in the individual series. Once the presence of the feature has been established, the second step of the procedure involves assessing whether it is common to the series under analysis. This is done by ascertaining whether there exists a linear combination of the series which does *not* have the feature. More specifically, take as an example the model

[29] A closely related and commonly applied procedure is that proposed by Blanchard and Katz (1992), who tackle the "common or region-specific shocks" issue focusing on employment instead. Specifically, they regress the first differences of the logarithms of regional employment levels on the first difference of the logarithms of the national employment level. See also Brunello et al. (2001) and Jimeno and Bentolila (1998).

[30] On this point see, among others, Chapman (1991) and Martin (1997).

[31] Dixon and Shepherd also argue against regressing the regional unemployment rates on the national, as part of the correlation will be "spurious". To avoid this problem, they suggest using regional bilateral comparisons. The initial proponents of the procedure were aware of the potential spuriousness problem, but argued against the view that it could invalidate its results. According to Brechling (1967), for instance, "There is, however, nothing spurious about the results on this account; on the contrary, the results would be deficient if they did not measure, amongst other things, the weight given to regional unemployment ratios" (p. 5). Furthermore, as the character of short-term policy intervention (e.g. monetary or fiscal policies) is mostly national, in our view, it is the region vis-à-vis nation relationship which conveys the most useful information from an economic policy viewpoint. We, thus, choose to focus on the latter, rather than on bilateral comparisons between regions.

[32] See also Vahid and Engle (1993, 1997).

$$y_t = x_t\beta + z_t\gamma + \varepsilon_t \tag{33}$$

where y_t is the variable under analysis, x_t could be a constant, relevant trends and/or other weakly exogenous variables and, in the case of serial correlation, z_t would simply be lags of y_t and possibly other variables. Then, the presence (absence) of the feature can be defined in terms of whether γ is (is not) significantly different from zero. That is:

$$\begin{aligned} &H_0 : \gamma = 0, \text{ No Feature} \\ &H_1 : \gamma \neq 0, \text{ Feature} \end{aligned} \tag{34}$$

and the *feature test* is the usual Lagrange Multiplier (LM) test of over-identifying restrictions, which has a limiting chi-squared distribution.

If two series y_1 and y_2 are both found to have the feature, it is then possible to assess whether the latter is common between them by testing whether there exists a λ such that $u_t = y_{1t} - \lambda y_{2t}$ does *not* have the feature. Engle and Kozichi (1993) show that an asymptotically valid estimate of λ can be obtained from the two-stage least squares (2SLS) regression of

$$y_{1t} = \lambda y_{2t} + x_t\beta + z_t\gamma + \varepsilon_t \tag{35}$$

where the instrument list is $\{x, z\}$. In its LM form, the *common-feature test* statistic can then be derived from the auxiliary regression of the 2SLS residuals on $\{x, z\}$ and computed as TR^2, i.e. as the product of the number of observations and the R^2 of the regression.

To better appreciate the difference between the BT and the EK methodologies, following Hall and Shepherd (2003), we can lay out the argument as follows. Consider the simple correlation coefficient between the two series U_R and U_N, respectively the regional and national unemployment rates

$$r_{U_R U_N} = \frac{\operatorname{cov}(U_R, U_N)}{\sigma_{U_R}\sigma_{U_N}} \tag{36}$$

Now, assume that the data generating processes for U_R and U_N are

$$U_R(t) = C_R(t) + e_R(t) \tag{37}$$

$$U_N(t) = C_N(t) + e_N(t) \tag{38}$$

The features C_R and C_N represent serial correlation processes, i.e. cycles, which may or may not be common, while e_R and e_N are contemporaneous shocks that may or may not be correlated. One can think of the cyclical component of unemployment as being dependent on the fluctuations of output about trend and, thus, being (mainly) demand-led, while the shocks may be considered as labour supply "disturbances", giving rise to temporary deviations of unemployment from equilibrium independently from the ups and downs of the business cycle, i.e. changes in frictional unemployment.

The formulations in (37) and (38) are based on the unobserved-component model and reflect the idea that the cyclical behaviour of a series is revealed by a well-defined serial correlation feature. This, in turn, suggests that it is possible to capture a predictable element in the series cycle, once the irregular-component has been taken account of.

If U_R and U_N are well described by (37) and (38), the correlation coefficient can be re-written as

$$r_{U_R U_N} = \frac{\operatorname{cov}\left[\left(C_R + e_R\right),\left(C_N + e_N\right)\right]}{\sigma\left(C_R + e_R\right)\sigma\left(C_N + e_N\right)} \tag{39}$$

To simplify matters, assume the cycles (i.e. the *C*'s) are uncorrelated with the contemporaneous shocks (i.e. the *e*'s). When that is so, the correlation coefficient becomes

$$r_{U_R U_N} = \frac{\operatorname{cov}\left(C_R, C_N\right) + \operatorname{cov}\left(e_R, e_N\right)}{\left[\operatorname{var}\left(C_R\right) + \operatorname{var}\left(e_R\right)\right]^{1/2}\left[\operatorname{var}\left(C_N\right) + \operatorname{var}\left(e_N\right)\right]^{1/2}} \tag{40}$$

Thus, the overall correlation between U_R and U_N depends on the values of the two covariances between the *C* terms and the *e* terms. If the series are characterised by different serial correlation processes (i.e. non-common cycles), there is no covariance between the C terms, and the correlation between U_R and U_N reflects the covariance between the contemporaneous shock terms e_R and e_N. However, if the cycles are common, i.e. $C_R = \lambda C_N$, the correlation between the regional and national unemployment rates will reflect both the covariance between the serial correlation terms and that between the contemporaneous shocks. Simply regressing U_R on U_N, as prescribed by the BT approach, does not allow one to establish how much of the observed co-movement is the result of common cycles and how much derives from common contemporaneous shocks.

The common-feature approach developed by EK directly tests whether the cycles are common or not. If the EK test cannot reject the common-cycle hypothesis, the implication is that unemployment rates respond fairly homogeneously to common demand disturbances across regions. As a result, national demand-management policies will be effective in reducing the short-term variation of regional unemployment in most cases. The opposite holds when the EK test does reject the common-cycle hypothesis, suggesting that regional unemployment rates are subject to region-specific demand shocks and/or react in a significantly different fashion to common shocks. The BT regressions, on the other hand, can be used to obtain an indication of how much of the contemporaneous shocks have a national character, i.e. to assess the extent to which frictional unemployment movements are common across regions.

The Engle-Kozichi and Brechling-Thirlwall techniques

In applying the EK technique to each Italian regional unemployment series, we start by testing for the presence of a serial correlation feature via the following bivariate VAR(1)[33]

$$
\begin{aligned}
U_{Rt}(t) &= \alpha_R + \delta_R U_{Nt}(t) + \beta_R U_{Rt}(t-1) + \phi_R U_{Nt}(t-1) + \theta_{84} + \theta_{92} + \varepsilon_R \\
U_{Nt}(t) &= \alpha_N + \delta_N U_{Rt}(t) + \beta_N U_{Rt}(t-1) + \phi_N U_{Nt}(t-1) + \theta_{84} + \theta_{92} + \varepsilon_N
\end{aligned}
\tag{41}
$$

[33] While it is also possible to test for serial correlation via running AR models for the individual series, the VAR models should be preferred as they allow for any system interdependence.

where, as before, θ_{84} and θ_{92} are the two intercept dummies introduced to deal with the 1984 and 1992 definition breaks in the series. In this framework, the feature test is an LM test on the significance of lagged unemployment rates, i.e. a test of whether lagged unemployment rates contain useful information for forecasting current unemployment rates.

When the presence of a serial correlation feature in the regional unemployment series cannot be rejected, we proceed to ascertaining whether this feature is common to the national rate. Using as instruments a constant, the two dummies, $U_{Rt}(t-1)$ and $U_{Nt}(t-1)$, the common-feature test is carried out via the 2SLS estimation of

$$U_{Rt}(t) = \lambda U_{Nt}(t) + \theta_{84} + \theta_{92} + \varepsilon_{Rt} \tag{42}$$

and the subsequent LM test of overidentifying restrictions, which is distributed as a chi-squared with one degree of freedom. To avoid the possibility that the results of the common-feature test may hinge on the normalisation imposed by the 2SLS procedure, the estimations are also carried out reversing the dependent and independent variables in (42).

The results reported in Table 6 show that the LM test rejects the null hypothesis of no serial correlation (cycle) feature at the 1 per cent level of significance in 17 regions and at the 5 per cent in the remaining 3. As for the national unemployment series, each of the 20 bivariate VAR regressions confirms the presence of a serial correlation feature at the 1 per cent significance level. Though all the regional series appear to be characterised by a cyclical behaviour, however, the common-feature test rejects the null hypothesis of a common cycle with the national unemployment rate in every single case. The chi-squared statistics are almost always significant at the 1 per cent level and the results are robust to the choice of the normalising variable[34].

The absence of a common serial correlation feature between the regional and national unemployment rates indicates that the cyclical patterns of the regional rates are sufficiently dissimilar across regions that they cannot be properly proxied by the short-term variation of their weighted average, i.e. the national cycle. As mentioned, the implication is that *national* economic policies will have fairly heterogeneous effects on the short-term volatility of *regional* unemployment rates. It is thus interesting to investigate further the determinants of this result.

[34] In only two cases, i.e. those of Valle d'Aosta and Liguria, the value of the chi-squared statistic drops consistently going from the feature- to the common-feature test, but still remains significant at the 5 per cent level.

Table 6 - Engle-Kozichi feature and common feature tests

	Dependent variable $U_{Rt}(t)$		Dependent variable $U_{Nt}(t)$	
Region	Feature Test	Common Feature Test	Feature Test	Common Feature Test
Piemonte	14.085^	17.231^	11.818^	15.864^
Valle d'Aosta	11.553^	5.556*	12.769^	8.696^
Lombardia	16.412^	18.523^	11.649^	15.148^
Trentino Alto Adige	16.540^	16.257^	11.712^	10.684^
Veneto	18.360^	21.375^	11.264^	17.612^
Friuli Venezia Giulia	19.878^	18.789^	13.041^	6.727^
Liguria	15.168^	12.769^	11.869^	6.118*
Emilia Romagna	21.009^	21.285^	12.045^	11.121^
Toscana	18.800^	18.994^	12.562^	9.238^
Umbria	10.578^	14.873^	11.172^	15.075^
Marche	11.283^	7.697^	11.157^	7.316^
Lazio	8.943^	10.742^	11.378^	12.519^
Abruzzo	9.020*	4.442*	11.412^	9.580^
Molise	13.715^	9.293^	14.169^	10.279^
Campania	11.670^	17.043^	11.207^	16.871^
Puglia	11.095^	18.796^	11.413^	18.829^
Basilicata	6.420*	17.505^	11.659^	19.359^
Calabria	13.286^	16.971^	12.822^	16.591^
Sicilia	16.706^	20.096^	11.237^	17.130^
Sardegna	7.582*	7.192^	11.161^	9.209^

Notes:
^ and * indicate, respectively, rejection at the 1% and 5% level of significance.

Strictly speaking, the absence of a common cycle may indicate that regional unemployment rates are subject to dissimilar demand shocks and/or are responding in a different fashion to common demand shocks, with some being more cyclically sensitive than others[35]. One rationale for the latter scenario is that regional structural differences may lead to different speeds of adjustment to the same aggregate shocks, the reason being that

[35] It is worth noting that the outcome of the common-feature tests may also depend on the fact that the hypothesis being tested by the EK procedure is a very stringent one. As noted by Ericsson (1993), the finding of a common-cycle implies that the impulse response functions (IRFs) of the variables under analysis are perfectly collinear. Vahid and Engle (1997) suggests that a reasonable alternative is that the cycles may be co-dependent, i.e. that the IRFs are not exactly collinear, but linearly dependent after one or more lags. They devise a test for co-dependent cycles, but this is impractical for time series as short as ours. A viable, though less satisfying, alternative to explore this issue is that of investigating the cross-correlations between the regional and national unemployment rates at different lag-lengths or, as proposed by Hall and Shepherd (2003), that of introducing further lags in the EK test and judge on the presence of one or more co-dependent cycles according to their significance.

unemployment may be diversely affected across regions if the shocks have a sectoral character. We briefly explore the latter possibility introducing the shares of total value added produced in agriculture, industry and services as additional exogenous variables in the EK regressions, to control for regional structural differences.

Table 7 – Engle-Kozichi feature and common feature tests with sector value-added shares

	Dependent variable $U_{Rt}(t)$		Dependent variable $U_{Nt}(t)$	
Region	Feature Test	Common Feature Test	Feature Test	Common Feature Test
Piemonte	10.476^	15.083^	9.770^	14.824^
Valle d'Aosta	13.923^	11.990^	14.711^	5.535*
Lombardia	15.706^	16.673^	9.290^	10.767^
Trentino Alto Adige	11.310^	17.922^	1.557	3.535**
Veneto	15.523^	22.827^	6.481*	18.960^
Friuli Venezia Giulia	14.199^	20.185^	5.726**	0.678
Liguria	7.175*	8.911^	5.213**	0.304
Emilia Romagna	20.020^	22.203^	8.063*	10.078^
Toscana	16.586^	19.748^	7.617^	6.430*
Umbria	5.339**	13.651^	6.089*	13.034^
Marche	2.839	4.167*	4.936**	11.929^
Lazio	4.942**	9.886^	15.933^	10.332^
Abruzzo	10.030^	14.647^	5.654*	0.207
Molise	12.996^	3.425**	16.409^	12.989^
Campania	7.790*	14.890^	9.702^	15.218^
Puglia	9.749^	15.208^	10.083^	15.273^
Basilicata	3.945	20.930^	7.205*	22.626^
Calabria	3.784	12.751^	8.673*	18.805^
Sicilia	11.925^	12.971^	9.696^	13.916^
Sardegna	7.717*	0.319	13.512^	16.308^

Notes:
^ , * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance.

From the estimates reported in Table 7 it appears that controlling for regional production structure differences goes some way in reducing the value of the chi-squared statistics, so that there is evidence for the absence of a cycle in at least five of the regional unemployment series. Moreover, the common feature test provides some evidence for a common-cycle for Friuli Venezia Giulia, Liguria, Abruzzo, Molise and Sardegna. However, in many respects, the results are now also much less clear-cut, e.g. in many cases, normalisation seems to matter and the common-test feature provides strong evidence of rejection even when the correspondent feature-test points to the absence of a feature in at least one of the series[36]. For these reasons, we do not place primary weight on the results in Table 7, which still show the EK common-feature test rejecting the hypothesis of a common cycle in nearly all cases.

The evidence gathered, thus, points to the alternative explanation for the rejection of the common-cycle hypothesis, i.e. that demand shocks are largely region-specific, as the most interesting. Indeed, using Blanchard and Katz's (1992) approach, Brunello et al. find that only about 30 per cent of demand shocks seem to be common across the Italian regions[37]. In an integrated economy, high labour mobility should ensure that the effects of region-specific shocks are fairly evenly distributed across regions, as workers migrate in or out of their regions following a positive or negative demand shock. However, Leonardi (2004) finds that, for the Italian regions in the 1960-1999 period, migration played a negligible role in the adjustment process following a region-specific demand shock, with the bulk of the correction coming about via changes in the participation rate (60-70 per cent) and the unemployment rate (around 30 per cent). Our finding that the regional unemployment cycles are significantly different from the national cycle is in line with this evidence.

The heterogeneity in the short-run volatility of regional unemployment will also be greater the more diverse the evolution of the frictional component of unemployment across regions, i.e. the more the above-defined contemporaneous shocks will have a region-specific, as opposed to national, character. We investigate this issue in a BT framework.

To avoid any possible influence of the serial correlation features in the regional and national unemployment rate series, the BT regressions are performed using first-differences of the variables, as the EK feature test cannot reject the null of no serial correlation in any of the latter[38].

Thus, adopting a log-linear structure, for each of the 20 Italian regions we estimate

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[36] In this case, the expectation is for the common-feature test not to reject the null hypothesis, as only one of the two series contains a feature.

[37] This figure falls to only about 16 per cent for the average Southern region, while it is about 41 per cent for the Northern region [see Brunello et al. (2001), Table 3, p. 112].

[38] Even if not sizeable enough to be picked up by the EK common-feature test as significant, any covariance between the regional and national serial correlation features will have an effect on the BT regressions R^2's, as equation (40) shows. First-differencing the variables eliminates serial correlation, so that the BT regressions R^2's will solely reflect covariance between contemporaneous shocks.

$$\Delta \ln U_{Rt}\left(t\right) = \beta \Delta \ln U_{Nt}\left(t\right) + \theta_{84} + \theta_{92} + \varepsilon_{Rt}$$

so that (β), the coefficient of regional sensitivity, provides the elasticity of the regional unemployment rate to the national one.

Table 7 – BT regressions, variables in logs, first differences

	Feature Test	BT regression		
Region		β	$H_{\beta=1}$	Adjusted R^2
Piemonte	2.389	1.450^	0.023	0.747
Valle d'Aosta	0.058	0.384	0.265	-0.083
Lombardia	0.058	1.326^	0.263	0.511
Trentino Alto Adige	0.507	1.048*	0.913	0.191
Veneto	1.642	1.252^	0.282	0.634
Friuli Venezia Giulia	1.409	0.832*	0.623	0.257
Liguria	0.048	0.811^	0.475	0.305
Emilia Romagna	1.423	0.574*	0.068	0.383
Toscana	3.100**	0.845^	0.308	0.696
Umbria	2.248	1.440^	0.043	0.692
Marche	3.575**	1.087^	0.670	0.624
Lazio	1.545	0.795^	0.256	0.465
Abruzzo	3.041**	0.951^	0.850	0.406
Molise	1.391	0.409	0.037	0.068
Campania	0.198	0.974^	0.888	0.588
Puglia	0.530	1.228^	0.027	0.889
Basilicata	3.053**	1.290^	0.348	0.468
Calabria	0.317	0.752^	0.353	0.221
Sicilia	1.031	0.807^	0.256	0.553
Sardegna	3.339**	0.531^	0.007	0.436
All regions		0.939		0.453
Northern regions		0.987		0.452
Southern regions		0.868		0.454

Notes:
^ , * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance;
$H_{\beta=1}$ is the p-value for the null hypothesis $\beta = 1$.

The results in Table 8 show that the β turns out to be significant in all cases except for the two small regions of Valle d'Aosta and Molise, and the hypothesis that the regional sensitivity coefficient is equal to one cannot be accepted only in a handful of cases at conventional significance levels. However, for the average Italian region only about 45% of the contemporaneous shocks are common and this holds also for the average Northern and Southern regions[39]. Thus, movements in frictional unemployment seem to be fairly diverse across regions as well.

To sum up, our analysis of the cyclical behaviour of regional unemployment led us to conclude that unemployment cycles are fairly diverse across regions, so much so that the EK test rejects the hypothesis of a common-cycle with the nation in all cases. Looking for a common-cycle controlling for regional production structure differences does not change the picture much, suggesting that region-specific demand shocks and low labour mobility are likely to lie at the heart of the heterogeneous cyclical behaviour of regional unemployment. Further, the BT regression results suggest that a varied evolution of frictional unemployment across regions adds to the observed heterogeneity in the short-term variation of regional unemployment rates.

8. Conclusion

This paper investigates the nature of regional unemployment in Italy, both in the long- and the short-run.

Taking as a starting point the evidence of growing disparities in the 1977-2003 years, we assess whether regional unemployment rates are diverging from each other in a non-stationary way, i.e. as a result of pure hysteresis. Because there seem to be geographical differences in the divergent pattern of unemployment, with the Southern regions' rates displaying greater divergence, we perform our analysis not only on absolute but, following Blanchard and Katz (1992) and others, also on relative unemployment rates.

Relying both on univariate and panel unit-root tests, we show that the finding of a unit root in the Italian regional unemployment rates, which previous studies provided evidence of, is largely dependent on the use of low power tests. Exploiting the greater power of panel unit

[39] In one excludes Valle d'Aosta and Molise, the average R^2's in the three cases rise to about 50 per cent.

root tests allows us to confidently reject the unit root and, thus, the pure hysteresis hypothesis. The implication of this result is that, however persistent, shocks to regional unemployment will be temporary, in the sense that unemployment will return to its natural rate or NAIRU in the long-run.

We, then, proceed to estimate the NAIRU for each of the 20 Italian regions. Our estimates of the regional NAIRUs turn out to be fairly precise, at least if compared to similar studies in the literature, and allow us to draw two interesting conclusions. Firstly, the hypothesis of a constant NAIRU between 1977 and 2003 is supported by the data for all of the Italian regions, with the possible exception of Abruzzo. Secondly, we find that there is a significant degree of heterogeneity among the regional NAIRUs. Thus, long-term regional unemployment disparities do seem to reflect structural or equilibrium unemployment differences across regions, as indicated by the results of the unit root tests.

This suggests that economic policy intervention aimed at reducing long-term regional unemployment differentials in Italy should, as much as possible, be region-specific in character. National policies, homogenous across regions, are likely to have diverse effects on the regional NAIRUs.

We, then, turn our attention to the short-term variation and cyclical behaviour of regional unemployment. Again, we find evidence pointing to a significant degree of heterogeneity. The EK test rejects the hypothesis of a common-cycle between regional and national unemployment for each of the 20 regions and the results do not change significantly when we control for regional production structure differences. We interpret this outcome as indicating that region-specific demand shocks play a major role in shaping the cyclical pattern of regional unemployment. Finally, the BT regressions show that more than half of the movements in frictional unemployment are region-specific, thus adding to heterogeneity in the short-term variation of regional unemployment. Just as noted for the reduction of structural unemployment, this suggests that the effects of national demand-management policies on the short-term variation of unemployment will be different across regions.

Bibliography

Amsler, C. and Lee, J. (1995) – "An LM Test for a Unit-root in the Presence of a Structural Change", *Econometric Theory*, 11, 359-368.

Arestis, P. and Mariscal, I. B. F. (1999) – "Unit Roots and Structural Breaks in OECD Unemployment", *Economics Letters*, 65, 149-156.

Banerjee, A., Lumsdaine, R. L. and Stock, J. H. (1992) – "Recursive and Sequential Tests of the Unit-Root and Trend-Break Hypotheses: Theory and International Evidence", Journal of Business and Economic Statistics, 10, 271-87.

Bean, C. (1992) – "European Unemployment: A Survey", *Centre for Economic Performance, Discussion Paper 71*.

Blanchard, O. and Katz, L. (1992) – "Regional Evolutions", *Brooking Papers on Economic Activity*, 1, 1-77.

Blanchard, O. and Summers, L. H. (1986) – "Hysteresis and the European Unemployment Problem", *NBER Macroeconomics Annual*, 1, 15-78.

Blanchard, O. and Summers, L. H. (1987) – "Hysteresis in Unemployment", *European Economic Review*, 31, 288-295.

Brechling, F. R. (1967) – "Trends and Cycles in British Regional Unemployment", *Oxford Economics Papers*, 19, 1-21.

Brunello, G., Lupi C. and Ordine, P. (2000) – "Regional Disparities and the Italian NAIRU", *Oxford Economic Papers*, 52, 146-177.

Brunello, G., Lupi C. and Ordine, P. (2001) – "Widening Differences in Italian Regional Unemployment", *Labour Economics*, 8, 103-129.

Camarero, M., Carrion-i-Silvestre, J. L. and 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* , forthcoming.

Carrion-i-Silvestre, J. L., del Barrio, T. And López-Bazo, E. (2004) – “Breaking the Panels. An Application to the GDP per Capita”, mimeo, AQR Research Group. Department of Economics, Statistics and Spanish Economy, University of Barcelona.

Casavola, P. and Sestito, P. (1994) – “La nuova indagine ISTAT sulle forze di lavoro”, *Lavoro e Relazioni Industriali*, 1, 179-195.

Chapman, P. (1991) – “The Dynamics of Regional Unemployment in the UK, 1974-89”, *Applied Economics*, 23, 59-64.

Decressin, J. and Fatás, A. (1995) – “Regional Labor Market Dynamics in Europe”, *European Economic Review*, 39, 1627-1655.

Dixon, R. and Shepherd, D. (2001) – “Trends and Cycles in Australian State and Territory Unemployment Rates”, *The Economic Record*, 77, 252-269.

Eichengreen, B. (1993) – “Labour Markets and European Monetary Unification”, in Masson, P., Taylor, M. (Eds.), *Policy Issues in the Operation of Currency Unions*, Cambridge Univ. Press, Cambridge.

Engle, R. F. and Kozichi, S. (1993) – “Testing for Common Features”, *Journal of Business and Economic Statistics*, 11, 369-380.

Ewing, B. T. and Wunnava, P. V. (2001) – “Unit Roots and Structural Breaks in North American Unemployment Rates”, *North American Journal of Economics and Finance*, 12, 273-282.

Friedman, M. (1968) – “The Role of Monetary Policy”, *American Economic Review*, 58, 1-17.

Gray, D. (2004) – “Persistent Regional Unemployment Differentials Revisited”, *Regional Studies*, 38, 167-176.

Hall and Shepherd (2003) – “Testing for Common Cycles in Money, Nominal Income and Prices”, *The Manchester School*, 68-84.

Hansen, B. E. (1992) – “Testing for parameter instability in linear models”, *Journal of Policy Modeling*, 14, 517-533.

Im, K. S., Pesaran, M. H. and and Shin, Y. (2003) – “Testing for Unit Roots in Heterogeneous Panels”, *Journal of Econometrics*, 115, 53-74.

Im, K., Lee, J. and Tieslau, M. (2005) – “Panel LM Unit-root Tests with Level Shifts”, *Oxford Bulletin of Economics and Statistics*, 67, 393-419.

Jimeno, F. J. and Bentolila, S. (1998) – “Regional Unemployment Persistence (Spain, 1976-1994)”, *Labour Economics*, 5, 25-51.

Johansen, K. (2002) – “Hysteresis in Unemployment: Evidence from Norwegian Counties”, Working Paper Series No. 6/2002, Department of Economics, Norwegian University of Science and Technology.

Jönsson, K. (2005) – “Cross-sectional Dependency and Size Distortion in a Small-sample Homogenous Panel Data Unit Root Test”, *Oxford Bulletin of Economics and Statistics*, 67, 369-392.

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

Lee, J. and Strazicich, M. (2003) – “Minimum LM Unit Root Test with Two Structural Breaks”, *The Review of Economics and Statistics*, 85, 1082-1089.

León-Ledesma, M. A. (2002) – “Unemployment Hysteresis in the US States and the EU”, *Bulletin of Economic Research*, 54, 95-103.

León-Ledesma, M. A. and McAdam, P. (2004) – "Unemployment, Hysteresis and Transition", *Scottish Journal of Political Economy*, 51, 377-401.

Leonardi, M. (2004) – "The Persistence of Italian Regional Unemployment: the Role of Migration and Wages", *Working Papers WTW*, Università degli Studi di Milano.

Leslie, D., Yonghao, P. and Wharton, A. (1995) – "Hysteresis versus Persistence in Unemployment: A Sceptical Note on Unit Root Tests", *Labour*, 9, 507-523.

Lumsdaine, R. and Papell, D. (1997) – "Multiple Trend Breaks and the Unit Root Hypothesis", *The Review of Economics and Statistics*, 79, 212-218.

Martin, R. (1997) – "Regional Unemployment Disparities and their Dynamics", *Regional Studies*, 31, 237-252.

Mitchell, W. F. (1993) – "Testing for Unit Roots and Persistence in OECD Unemployment Rates", *Applied Economics*, 25, 1489-1501.

Moon, R. H. and Perron, B. (2004) – "Testing for a Unit Root in Panels with Dynamic Factors", *Journal of Econometrics*, 122, 81-126.

Murray, C. J. and Papell, D. H. (2000) – "Testing for Unit Roots in Panels in the Presence of Structural Change with an Application to OECD unemployment", in Baltagi, B. H. (ed.), *Nonstationary Panels, Panel Cointegration and Dynamic Panels, Advances in Econometrics*, 15, JAI Press, 223-238.

Nelson, C. R. and Plosser, C. I. (1982) – "Trends and Random Walks in Macroeconomic Time Series", *Journal of Monetary Economics*, 10, 139-162.

O'Connel, P. G. J. (1998) – "The Overvaluation of Purchasing Power Parity", *Journal of International Economics*, 44, 1-19.

Papell, D. H., Murray, C. J. and Ghiblawi, H. (2000) – "The Structure of Unemployment", *The Review of Economics and Statistics*, 82, 309-315.

Payne J. E., Ewing, B. T. and George, E. P. (1999) –"Time Series Dynamics of US State Unemployment Rates", *Applied Economics*, 31, 1503-1510.

Perron, P. (1989) – "The Great Crash, the Oil Price Shock and the Unit Root Hypothesis", *Econometrica*, 57, 1361-1401.

Perron, P. (1990) – "Testing for a Unit Root in a Time Series with a Changing Mean", *Journal of Business & Economic Statistics*, 8, 153-162.

Perron, P. (1997) – "Further Evidence on Breaking Trend Functions in Macroeconomic Variables", *Journal of Econometrics*, 80, 355-385.

Perron, P. and Vogelsang, T. J. (1992a) – "Nonstationarity and Level Shifts with an Application to Purchasing Power Parity", *Journal of Business & Economic Statistics*, 10, 301-320.

Perron, P. and Vogelsang, T. J. (1992b) – "Testing for a Unit Root in a Time Series with a Changing Mean: Corrections and Extensions", *Journal of Business & Economic Statistics*, 10, 467-470.

Pesaran, M. H. (2005) – "A Simple Panel Unit Root Test in the Presence of Cross Section Dependence", *Cambridge University DAE Working Paper, number 0346*.

Pesaran, M. H. and Smith, R. (1995) – "Estimating Long-run Relationships from Dynamic Heterogeneous Panels", *Journal of Econometrics*, 68, 79-113.

Pesaran, M. H., Smith, R. And Im, K. S. (1996) – "Dynamic Linear Models for Heterogeneous Panels", in L. Matyas and P. Sevestre (eds.), *The Econometrics of Panel Data*, 2nd edition, Kluwer Academic Publishers, Amsterdam.

Phelps, E. S. (1967) – “Phillips Curves, Expectations of Inflation and Optimal Unemployment over Time”, *Economica*, 2, 22-44.

Phelps, E. S. (1968) – “Money-Wage Dynamics and Labor Market Equilibrium”, *Journal of Political Economy*, 76, 678-711.

Phelps, E. S. (1972) – “Inflation Policy and Unemployment Theory”, W. W. Norton and Co., New York.

Phillips, P. C. B. and Sul, D. (2003) – “Dynamic Panel Estimation and Homogeneity Testing Under Cross Section Dependence”, *Econometrics Journal*, 6, 217-259.

Røed, K. (1996) – “Unemployment Hysteresis – Macro Evidence from 16 OECD Countries”, *Empirical Economics*, 21, 589-600.

Røed, K. (1997) – “Hysteresis in Unemployment”, *Journal of Economic Surveys*, 11, 389-416.

Schmidt, P. and Phillips, P. C. B. (1992) – “LM Tests for a Unit Root in the Presence of Deterministic Trends”, *Oxford Bulletin of Economics and Statistics*, 54, 257-287.

Song, F. M. and Wu, Y. (1997) – “Hysteresis in Unemployment: Evidence from 48 States”, *Economic Enquiry*, 35, 235-244.

Song, F. M. and Wu, Y. (1998) – “Hysteresis in Unemployment: Evidence from OECD Countries”, *The Quarterly Review of Economics and Finance*, 38, 181-192.

Strazicich, M. C., Tieslau, M. and Lee, J. (2001) – Hysteresis in Unemployment? Evidence from Panel Unit Root Tests with Structural Change”, *Unpublished manuscript, University of North Texas*.

Thirlwall, A. P. (1966) – “Regional Unemployment as a Cyclical Phenomenon”, *Scottish Journal of Political Economy*, 13, 205-219.

Thirlwall, A. P. (1983) – “What are Estimates of the Natural Rate of Unemployment Measuring?”, *Oxford Bulletin of Economics and Statistics*, 45, 173-179.

Trivellato, U. (1993) – “La conta dei disoccupati: evidenze e interrogativi dalle nuove stime della Rilevazione sulle Forze di Lavoro”, *Rassegna di Statistiche del Lavoro*, 1, 85-93.

Vahid, F. and Engle, R. F. (1993) – “Common Trends and Common Cycles”, *Journal of Applied Econometrics*, 8, 341-360.

Vahid, F. and Engle, R. F. (1997) – “Codependent Cycles”, *Journal of Econometrics*, 80, 199-221.

Zivot, E. and Andrews, D. W. K. (1992) – “Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis”, *International Economic Review*, 39, 1073-1100.

Appendix

Table A1 – Perron (1989) test on regional unemployment rates, 1984-2003, TB = 1992

Region	MODEL A – AO			MODEL B – IO1			MODEL C – IO2		
	k	T-ratio	Root (half life)	K	T-ratio	Root (half life)	k	T-ratio	Root (half life)
Piemonte	0	-2.081	0.403 (0.763)	0	-2.103	0.329 (0.623)	0	-2.071	0.437 (0.837)
Valle d'Aosta	0	-3.256	0.194 (0.422)	0	-3.701**	0.283 (0.548)	0	-3.345	0.154 (0.370)
Lombardia	0	-1.997	0.250 (0.499)	0	-1.084	0.431 (0.824)	0	-1.081	0.434 (0.830)
Trentino Alto Adige	0	-2.072	0.512 (1.034)	0	-2.504	0.075 (0.268)	0	-2.467	0.069 (0.259)
Veneto	0	-2.790	0.243 (0.490)	0	-1.942	-0.086 (-)	0	-1.702	0.052 (0.234)
Friuli Venezia Giulia	0	-3.458**	0.211 (0.445)	0	-2.820	0.369 (0.694)	0	-3.301	0.212 (0.447)
Liguria	0	-1.267	0.738 (2.280)	0	-1.994	0.575 (1.252)	0	-3.243	0.440 (0.843)
Emilia Romagna	0	-1.997	0.492 (0.976)	0	-0.792	0.732 (2.225)	1	-1.953	0.211 (0.445)
Toscana	0	-0.749	0.807 (3.239)	0	-2.378	0.312 (0.595)	0	-2.423	0.399 (0.754)
Umbria	0	-2.782	0.377 (0.710)	0	-3.325	0.077 (0.270)	1	-3.309	0.256 (0.508)
Marche	0	-1.438	0.529 (1.089)	0	-3.196	0.095 (0.294)	3	-2.256	-0.606 (-)
Lazio	0	-1.227	0.786 (2.886)	0	-2.303	0.405 (0.767)	0	-3.142	0.490 (0.973)
Abruzzo	0	-2.031	0.483 (0.953)	0	-3.511	0.114 (0.318)	0	-2.750	0.275 (0.537)
Molise	0	-0.864	0.855 (4.442)	0	-2.455	0.400 (0.756)	0	-4.888*	0.218 (0.455)
Campania	1	-3.148	0.468 (0.911)	0	-2.485	0.398 (0.752)	2	-3.694	0.053 (0.235)
Puglia	0	-0.885	0.848 (4.211)	0	-2.088	0.513 (1.039)	2	-2.925	0.272 (0.531)
Basilicata	0	-2.598	0.608 (1.394)	0	-5.857^	-0.001 (-)	0	-3.559	0.364 (0.685)
Calabria	0	-1.129	0.763 (2.560)	1	-3.313	0.045 (0.223)	0	-1.220	0.715 (2.069)
Sicilia	2	-1.268	0.776 (2.732)	1	-2.293	0.186 (0.411)	2	-1.971	0.218 (0.455)
Sardegna	0	-2.484	0.283 (0.549)	0	-2.849	0.070 (0.260)	0	-2.045	0.384 (0.724)
North	0	-1.965	0.352 (0.664)	0	-1.769	0.370 (0.696)	0	-1.891	0.427 (0.814)
South	0	-3.035	0.249 (0.499)	0	-3.560	0.232 (0.475)	1	-3.888	-0.105 (-)
Italy	0	-1.021	0.776 (2.734)	0	-2.701	0.273 (0.534)	0	-2.257	0.550 (1.159)

*Notes: * and ** indicate, respectively, rejection at the 5% and 10% level of significance.*

Table A2 – Perron (1990) test on regional unemployment rates, 1984-2003, TB = 1992

Region	MODEL A - AO			MODEL B – IO		
	k	T-ratio	Root (half life)	k	T-ratio	Root (half life)
Piemonte	2	-2.891	0.572 (1.241)	0	-0.852	0.832 (3.780)
Valle d'Aosta	0	-1.981	0.590 (1.313)	0	-1.805	0.604 (1.376)
Lombardia	2	-3.054	0.630 (1.890)	0	-1.372	0.760 (2.534)
Trentino Alto Adige	2	-2.880	0.548 (1.153)	0	-1.381	0.803 (3.155)
Veneto	1	-1.701	0.815 (3.388)	0	-1.904	0.744 (2.344)
Friuli Venezia Giulia	1	-1.412	0.823 (3.568)	1	-1.108	0.819 (3.470)
Liguria	0	-0.637	0.893 (6.140)	0	-0.458	0.919 (8.223)
Emilia Romagna	1	-1.788	0.781 (2.799)	0	-1.180	0.869 (4.927)
Toscana	1	-1.164	0.854 (4.390)	0	-0.215	0.967 (20.950)
Umbria	4	-4.518^	-0.075 (-)	2	0.049	1.012 (55.800)
Marche	0	-1.336	0.686 (1.843)	0	-1.039	0.742 (2.321)
Lazio	0	-1.392	0.746 (2.363)	0	-1.211	0.768 (2.630)
Abruzzo	0	-1.648	0.618 (-1.439)	0	-1.371	0.664 (1.695)
Molise	0	-1.334	0.781 (2.805)	0	-1.149	0.806 (3.215)
Campania	1	-4.417^	0.349 (0.659)	0	-2.143	0.667 (1.713)
Puglia	1	-2.815	0.558 (1.188)	0	-1.379	0.768 (2.628)
Basilicata	0	-3.199**	0.511 (1.032)	0	-3.150**	0.577 (1.259)
Calabria	4	-3.971*	-0.161 (-)	0	-2.406	0.705 (1.979)
Sicilia	0	-1.633	0.793 (2.993)	0	-1.470	0.833 (3.796)
Sardegna	0	-2.226	0.372 (0.702)	0	-1.988	0.385 (0.726)
North	2	-3.498*	0.703 (1.964)	0	-0.672	0.888 (5.860)
South	0	-3.199**	0.333 (0.631)	0	-1.802	0.765 (2.590)
Italy	2	-1.411	0.661 (1.674)	0	-0.670	0.850 (4.264)

*Notes: ^ , * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance.*

Table A3 – Perron (1989) test on relative regional unemployment rates, 1984-2003, TB = 1992.

Region	MODEL A – AO			MODEL B – IO1			MODEL C – IO2		
	k	T-ratio	Root (half life)	K	T-ratio	Root (half life)	k	T-ratio	Root (half life)
Piemonte	1	-3.061	0.243 (0.489)	0	-1.474	0.534 (1.105)	1	-1.326	0.517 (1.050)
Valle d'Aosta	0	-3.881*	-0.115 (-)	0	-5.820^	-0.021 (-)	0	-3.799	-0.122 (-)
Lombardia	0	-1.049	0.750 (2.409)	2	0.166	1.062 (11.394)	0	0.574	1.286 (2.758)
Trentino Alto Adige	0	-1.220	0.775 (2.716)	1	-0.816	0.724 (2.150)	0	-1.891	0.329 (0.624)
Veneto	0	-1.920	0.724 (2.146)	0	0.073	1.027 (26.385)	0	0.569	1.218 (3.519)
Friuli Venezia Giulia	0	-1.013	0.702 (1.963)	0	-5.743^	-0.028 (-)	0	-2.558	0.057 (0.241)
Liguria	0	-2.330	0.455 (0.880)	5	-1.868	0.128 (0.337)	0	-4.843^	0.108 (0.311)
Emilia Romagna	0	-1.701	0.761 (2.535)	4	-5.079^	-0.335 (-)	0	-0.582	0.842 (4.036)
Toscana	0	-2.009	0.482 (0.949)	1	-4.708^	-0.125 (-)	1	-2.381	0.046 (0.224)
Umbria	0	-3.188	0.362 (0.683)	0	-2.643	0.308 (0.588)	0	-2.739	0.371 (0.698)
Marche	3	-4.371^	-4.124 (-)	3	-4.691^	-2.654 (-)	3	-4.935^	-3.604 (-)
Lazio	1	-4.469^	-0.153 (-)	1	-5.695^	-0.378 (-)	1	-5.509^	-0.385 (-)
Abruzzo	0	-3.639**	0.067 (0.256)	0	-3.655**	0.044 (0.222)	0	-3.568	0.028 (0.193)
Molise	0	-2.270	0.446 (0.860)	0	-4.263^	-0.061 (-)	0	-4.453^	-0.310 (-)
Campania	0	-2.157	0.525 (1.077)	5	-1.082	0.268 (0.527)	5	-0.121	0.844 (4.078)
Puglia	1	-3.373	0.450 (0.868)	1	-3.691**	0.338 (0.639)	1	-3.190	0.440 (0.844)
Basilicata	0	-4.559^	0.284 (0.550)	0	-5.214^	0.168 (0.389)	0	-3.454	0.265 (0.522)
Calabria	0	-1.302	0.549 (1.156)	3	-3.274	0.408 (0.772)	1	-2.049	0.225 (0.464)
Sicilia	3	-5.622^	-0.080 (-)	0	-1.226	0.530 (1.090)	0	-1.227	0.508 (1.024)
Sardegna	0	-1.625	0.677 (1.775)	0	-2.713	0.304 (0.582)	0	-2.741	0.321 (0.609)
Italy			0.189 (0.416)			0.112 (0.317)			0.149 (0.364)
North	1	-2.180	0.712 (2.042)	2	-0.313	0.920 (8.368)	0	1.211	1.378 (2.159)
South	0	-3.237	0.503 (1.008)	0	-2.550	0.618 (1.440)	0	-3.089	0.474 (0.928)

*Notes: Reported roots for "Italy" are averages of regional values; ^ , * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance.*

Table A4 – Perron (1990) test on relative regional unemployment rates, 1984-2003, TB = 1992.

Region	MODEL A – AO			MODEL B - IO		
	k	T-ratio	Root (half life)	k	T-ratio	Root (half life)
Piemonte	2	-3.176**	0.449 (0.866)	1	-2.234	0.689 (1.863)
Valle d'Aosta	0	-2.752	0.408 (0.774)	0	-2.500	0.439 (0.843)
Lombardia	1	-3.355**	0.723 (2.139)	0	-2.081	0.759 (2.511)
Trentino Alto Adige	2	-3.370**	0.455 (0.879)	0	-1.602	0.815 (3.397)
Veneto	1	-2.442	0.760 (2.524)	0	-3.390**	0.744 (2.343)
Friuli Venezia Giulia	0	-1.350	0.859 (4.558)	4	-2.481	0.526 (1.080)
Liguria	0	-1.511	0.754 (2.454)	0	-1.316	0.784 (2.847)
Emilia Romagna	0	-2.347	0.778 (2.755)	0	-2.788	0.809 (3.271)
Toscana	0	-2.200	0.775 (2.726)	0	-2.433	0.813 (3.345)
Umbria	1	-3.225**	0.522 (1.067)	0	-1.584	0.758 (2.503)
Marche	0	-2.833	0.441 (0.848)	0	-2.608	0.473 (0.925)
Lazio	1	-3.770*	0.005 (0.133)	1	-4.112^	0.052 (0.234)
Abruzzo	0	-2.985	0.298 (0.572)	0	-2.727	0.321 (0.609)
Molise	0	-2.367	0.633 (1.101)	0	-2.222	0.537 (1.113)
Campania	1	-3.877*	0.492 (0.978)	0	-2.174	0.729 (2.196)
Puglia	1	-3.641*	0.571 (1.239)	1	-3.596*	0.638 (1.545)
Basilicata	0	-3.489*	0.489 (0.970)	0	-3.557*	0.530 (1.093)
Calabria	1	-1.848	0.774 (2.706)	0	-1.084	0.873 (5.124)
Sicilia	1	-1.590	0.795 (3.030)	0	-1.457	0.838 (3.926)
Sardegna	0	-1.740	0.681 (1.807)	0	-1.581	0.697 (1.917)
Italy			0.583 (1.285)			0.641 (1.560)
North	1	-3.157**	0.763 (2.561)	1	-4.924^	0.764 (2.577)
South	1	-4.455^	0.261 (0.516)	0	-2.065	0.844 (2.577)

*Notes: Reported roots for "Italy" are averages of regional values; ^, * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance.*

Table A5– Pesaran (2005) CADF* and CIPS* tests on regional unemployment rates, 1993-2003.

Region	**With intercept**			**With intercept and trend**		
	k	T-ratio	Root (half life)	k	T-ratio	Root (half life)
Piemonte	0	-1.771	0.814 (3.370)	0	-1.757	0.698 (1.929)
Valle d'Aosta	1	-6.190^	0.073 (-)	0	-1.408	0.096 (0.295)
Lombardia	0	-1.754	0.787 (2.894)	0	-3.203	0.374 (0.704)
Trentino Alto Adige	2	-6.190^	-0.692 (-)	0	-2.419	0.101 (0.302)
Veneto	1	-6.190^	0.683 (1.816)	1	-5.058*	0.586 (1.297)
Friuli Venezia Giulia	0	-2.380	0.751 (2.419)	0	-2.004	0.460 (0.893)
Liguria	0	-2.486	0.874 (5.158)	0	-1.542	0.843 (4.054)
Emilia Romagna	0	-0.615	0.899 (6.490)	0	-1.870	0.429 (0.819)
Toscana	0	-2.080	0.878 (5.328)	0	-0.725	0.895 (6.219)
Umbria	0	-1.905	0.767 (0.767)	0	-2.868	0.559 (1.192)
Marche	0	-0.765	0.806 (3.222)	0	-1.475	0.439 (0.841)
Lazio	0	-0.406	0.935 (10.234)	0	-1.545	0.630 (1.502)
Abruzzo	0	-0.668	0.859 (4.566)	0	0.033	1.015 (47.945)
Molise	1	0.471	1.083 (8.672)	0	-2.991	0.399 (0.754)
Campania	0	-0.498	0.879 (5.370)	1	-6.190*	0.198 (0.428)
Puglia	0	0.248	1.038 (18.867)	0	0.193	1.037 (18.987)
Basilicata	0	-2.191	0.590 (1.316)	0	-2.417	0.502 (1.007)
Calabria	0	-0.529	0.725 (2.157)	0	-0.283	0.837 (3.900)
Sicilia	0	0.516	1.098 (7.448)	0	0.080	1.022 (32.497)
Sardegna	0	1.363	1.365 (2.226)	0	0.465	1.239 (3.235)
CIPS*						
All regions		-1.701	0.761 (2.533)		-1.849	0.618 (1.440)
North		-2.728*	0.631 (1.507)		-2.156	0.509 (1.027)
South		-0.161	0.955 (14.927)		-1.389	0.781 (2.806)

Notes: CIPS roots are averages of CADF* regressions estimates; ^ , * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance.*

Table A6 – Pesaran (2005) CADF* and CIPS* tests on relative regional unemployment rates, 1993-2003.

Region	With intercept			With intercept and trend		
	k	T-ratio	Root (half life)	k	T-ratio	Root (half life)
Piemonte	0	-0.529	0.891 (6.020)	0	-2.349	0.234 (0.477)
Valle d'Aosta	0	-1.853	0.302 (0.579)	0	-3.029	-0.395 (-)
Lombardia	0	-1.524	0.826 (3.636)	0	-0.604	0.710 (2.020)
Trentino Alto Adige	0	-1.314	0.805 (3.203)	0	-1.068	0.586 (1.298)
Veneto	0	-1.237	0.801 (3.132)	0	-1.213	0.396 (0.749)
Friuli Venezia Giulia	0	-0.928	0.901 (6.678)	0	0.007	1.005 (135.953)
Liguria	2	-5.481*	0.463 (0.900)	0	-1.859	0.511 (1.032)
Emilia Romagna	0	-1.597	0.798 (3.078)	0	-2.282	0.056 (0.240)
Toscana	0	-1.190	0.899 (6.532)	1	-4.461**	-0.444 (-)
Umbria	0	-0.438	0.885 (5.686)	0	-2.537	0.328 (0.622)
Marche	0	-1.425	0.595 (1.335)	0	-3.553	-0.265 (-)
Lazio	1	-5.700*	-1.102 (-)	0	-4.820**	-1.222 (-)
Abruzzo	0	-0.667	0.766 (2.601)	0	-1.421	0.375 (-0.706)
Molise	0	-6.190^	-0.456 (-)	0	-6.383*	-0.456 (-)
Campania	0	-0.984	0.811 (3.314)	0	-1.828	0.264 (-0.521)
Puglia	1	-2.241	0.596 (1.340)	1	-2.373	0.388 (0.732)
Basilicata	0	-0.189	0.930 (9.560)	0	-1.399	0.266 (0.523)
Calabria	0	-0.481	0.932 (9.833)	0	-3.270	-0.013 (-)
Sicilia	0	0.275	1.038 (18.746)	0	-4.106**	-0.077 (-)
Sardegna	2	-3.760**	0.191 (0.418)	0	-1.716	0.498 (0.994)
CIPS*						
All regions		-1.873	0.594 (1.329)		-2.513	0.137 (0.349)
North		-1.935	0.589 (1.308)		-2.314	0.125 (0.333)
South		-1.780	0.601 (1.361)		-2.812	0.156 (0.373)

Notes: CIPS roots are averages of CADF* regressions estimates; ^ , * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance.*

Table A7 - Im et al. (2005) test, 1984-2003.

Region	Absolute Regional Unemployment Rates			Relative Regional Unemployment Rates		
	k	T-ratio	Root (half life)	k	T-ratio	Root (half life)
Piemonte	2	-4.000^	0.255 (0.508)	2	-3.195*	0.469 (0.914)
Valle d'Aosta	0	-1.899	0.632 (1.512)	1	-4.499^	-0.604 (-)
Lombardia	1	-3.362*	0.587 (1.299)	1	-3.156**	0.483 (0.952)
Trentino Alto Adige	1	-2.936**	0.683 (1.816)	2	-2.966**	0.509 (1.026)
Veneto	2	--1.223	0.800 (3.102)	1	-1.771	0.688 (1.857)
Friuli Venezia Giulia	0	-1.167	0.843 (4.058)	2	-2.937**	0.344 (0.650)
Liguria	0	-2.189	0.539 (1.121)	1	-1.595	0.726 (2.162)
Emilia Romagna	1	-1.935	0.721 (2.116)	1	-2.152	0.681 (1.803)
Toscana	0	-2.105	0.899 (6.532)	0	-2.267	0.514 (1.041)
Umbria	0	-1.862	0.644 (1.574)	0	-1.533	0.744 (2.344)
Marche	0	-2.779	0.349 (0.658)	0	-3.105**	0.248 (-0.497)
Lazio	1	-4.319^	0.027 (0.191)	1	-3.864*	0.068 (0.258)
Abruzzo	0	-3.542*	0.121 (0.328)	0	-3.645*	0.093 (0.292)
Molise	0	-2.020	0.593 (1.328)	0	-2.371	0.480 (0.945)
Campania	1	-3.741*	0.351 (0.662)	1	-3.465*	0.322 (0.612)
Puglia	1	-2.793	0.635 (1.525)	1	3.139**	0.481 (0.947)
Basilicata	0	-1.646	0.710 (2.026)	0	-1.496	0.754 (2.460)
Calabria	3	-4.213^	-0.231 (-)	1	-1.475	0.761 (2.533)
Sicilia	1	-2.647	0.632 (1.508)	1	-2.792	0.541 (1.128)
Sardegna	0	-2.027	0.591 (1.319)	1	-1.678	0.701 (1.950)
Panel unit root test						
All regions		-3.591^	0.519 (1.057)		-4.649^	0.450 (0.868)
North		-1.634	0.581 (1.279)		-4.178^	0.406 (0.769)
South		-3.664^	0.425 (0.811)		-2.232*	0.517 (1.049)

*Notes: ^, * and ** indicate, respectively, rejection at the 1%, 5% and 10% level of significance.*

Figure 1A – Regional unemployment rates

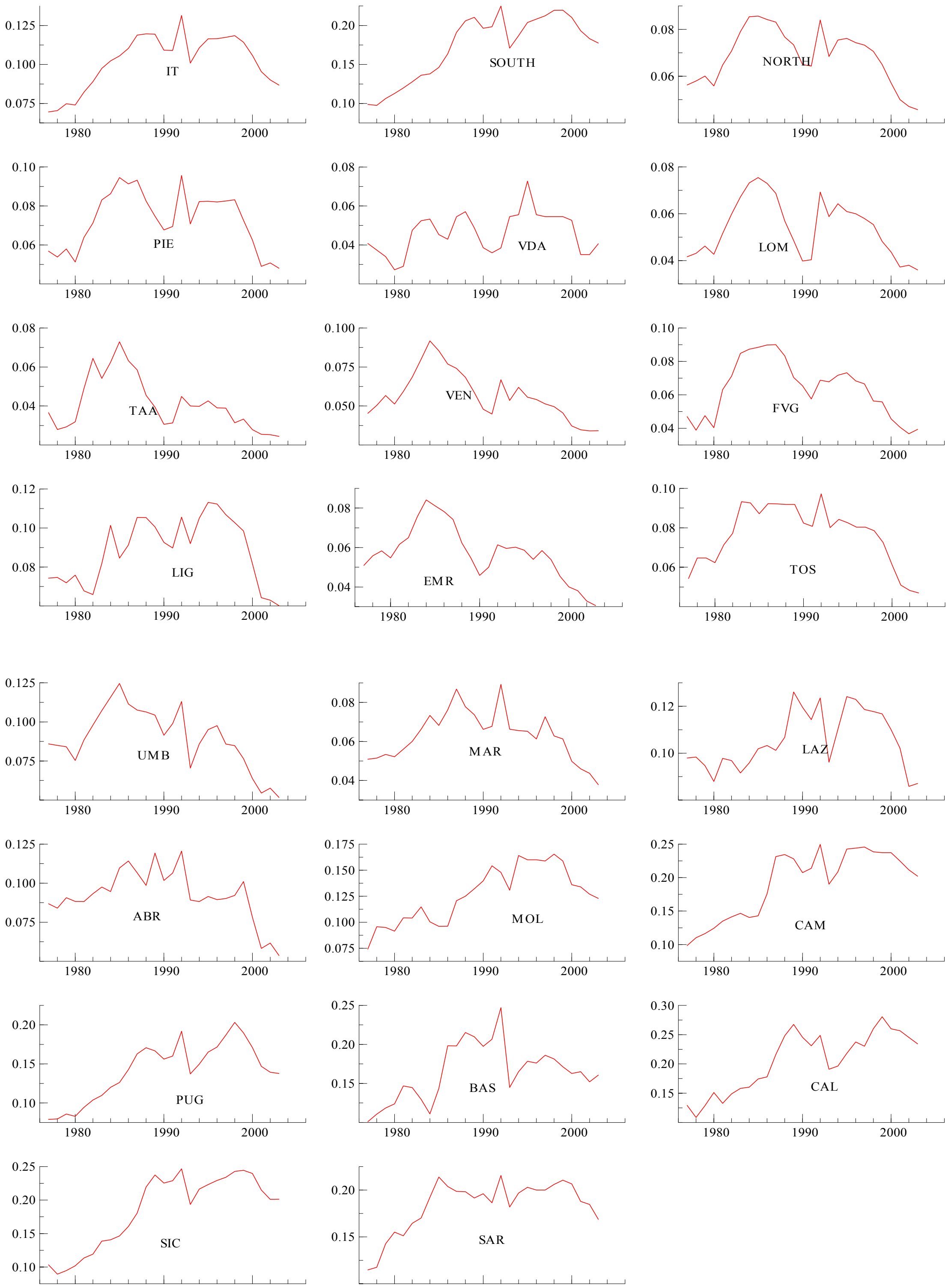

Figure 2A – Relative regional unemployment rates

Figure 3A – Regional NAIRUs, recursive estimates (broken-line) and +/- 2SE-band.

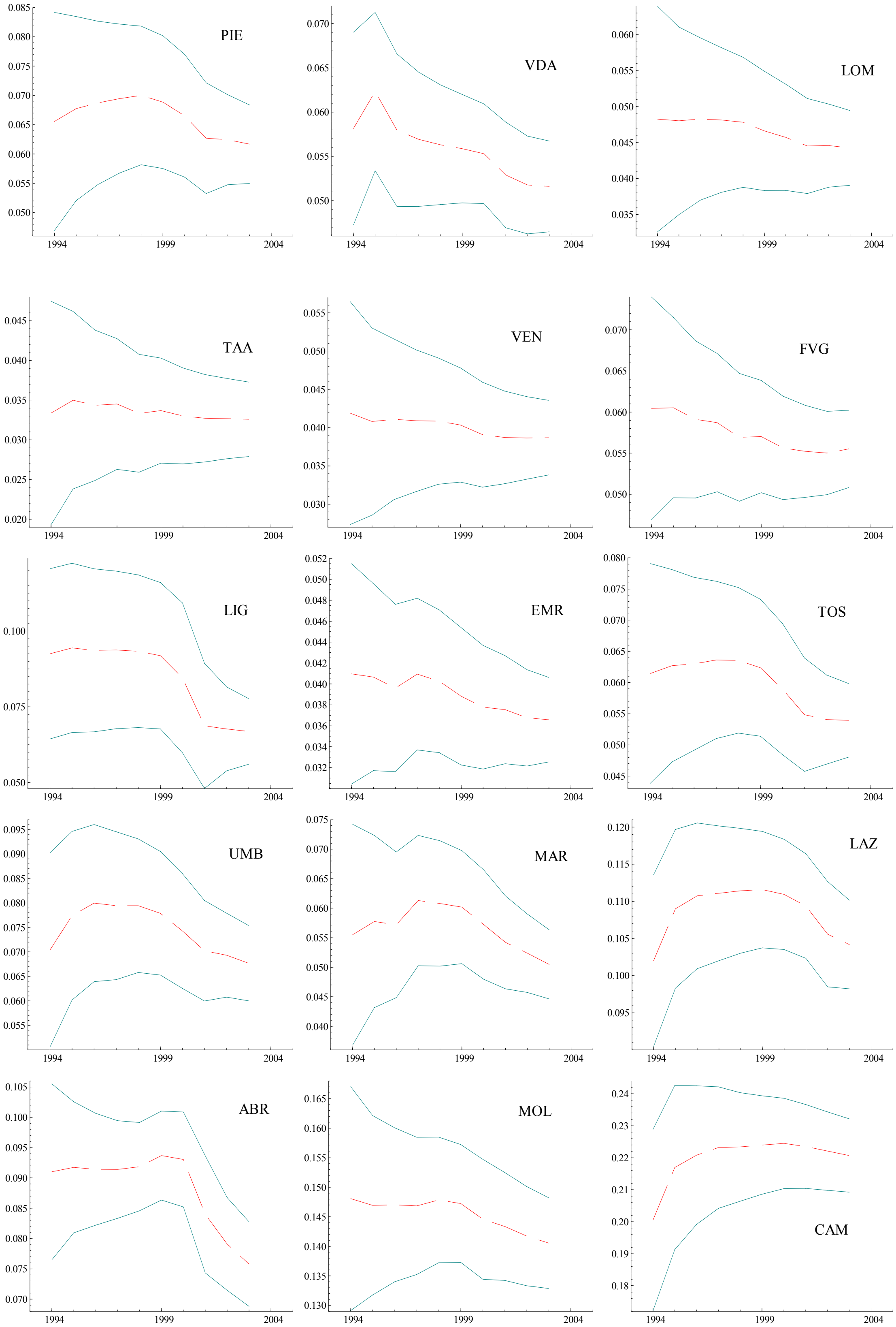

Figure 3A – Continued.