Long-Run Trends in Internal Migrations in Italy: a Study in Panel Cointegration with Dependent Units

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Abstract

The objective of this paper is to examine the long-run determinants of internal migrations from South Italy, and, in order to accomplish this task, to develop a bootstrap test for panel cointegration analysis with dependent units. Monte Carlo simulations show that the test, based on the Continuous-Path Block bootstrap, has good power and size properties and is robust to both short- and long-run dependence across units. The empirical analysis points to income in the sending region as a key factor of the decline of migrations, with unemployment and income differentials playing only a minor role.

Keywords: Migrations, Panel Cointegration, Continuous-Path Block Bootstrap, Italy.

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1 Introduction[1]

South Italy has a history of mass emigration stretching from the end of the XIX century to the late 1960s, when migrations abroad became negligible and internal migrations started to decline (see *e.g.*, Daveri and Faini, 1999). Except for two short-lived episodes in the early 1980s and 1990s[2], the negative trend in internal migrations continued for all the following decades: annual migration flows from the South to the rest of the country more than halved between the early '70s and the mid'90s, dropping from over 40,000 units to slightly less than 19,000 (see Fig. 1). Over the same period the labour market conditions in the south worsened significantly both in absolute and relative terms. The unemployment rate, around 10% in the late '70s, by the late 1980s doubled to about 20%, whereas in the Central and Northern regions it never reached 10% of the labour force (see Fig. 2 and Table 2). The unemployment figures are even more impressive if we consider that throughout the period the overall impact of unemployment compensation is likely to have been negligible[3]. Income in the South did grow, but at a slower rate than in the North, so that regional disparities as measured by GDP per capita also increased (see Fig. 3 and Table 1). Taking into account the role of the welfare state changes the picture only partially: the gap in disposable income including public transfers (for instance, disability pensions, very common in the South: cf. Attanasio e Padoa-Schioppa, 1991), although lower than that in GDP per head, remained approximately

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[2]In fact, these may be pure statistical artifacts. The local population registers, source of migration data, undergo a general revision after the population censuses, in the first year of each decade. Hence, all migrants who failed to notify the change of place of residence in the years before a census appear as migrating immediately afterwards.

[3]Although a precise assessment is difficult (the Italian unemployment benefit system is very complex, with a variety of different schemes, often operating at partially overlapping times and addressed at different parts of the labour force; see OECD, 2004), two main elements support this claim: (*i*) unemployment compensation is traditionally very low in Italy: in 1996, with a 12.1% unemployment rate, the total amounted to just 0.7% of GDP (for a comparison, in the European Union, with a 10.9% unemployment rate, it was 1.9% of GDP); (*ii*) further, only people who lost a job are eligible, so that a large fraction of young unemployed (60% of the total in South Italy in 1996 and the most likely to migrate: see Fig. 4) are excluded.

constant throughout the period[4].

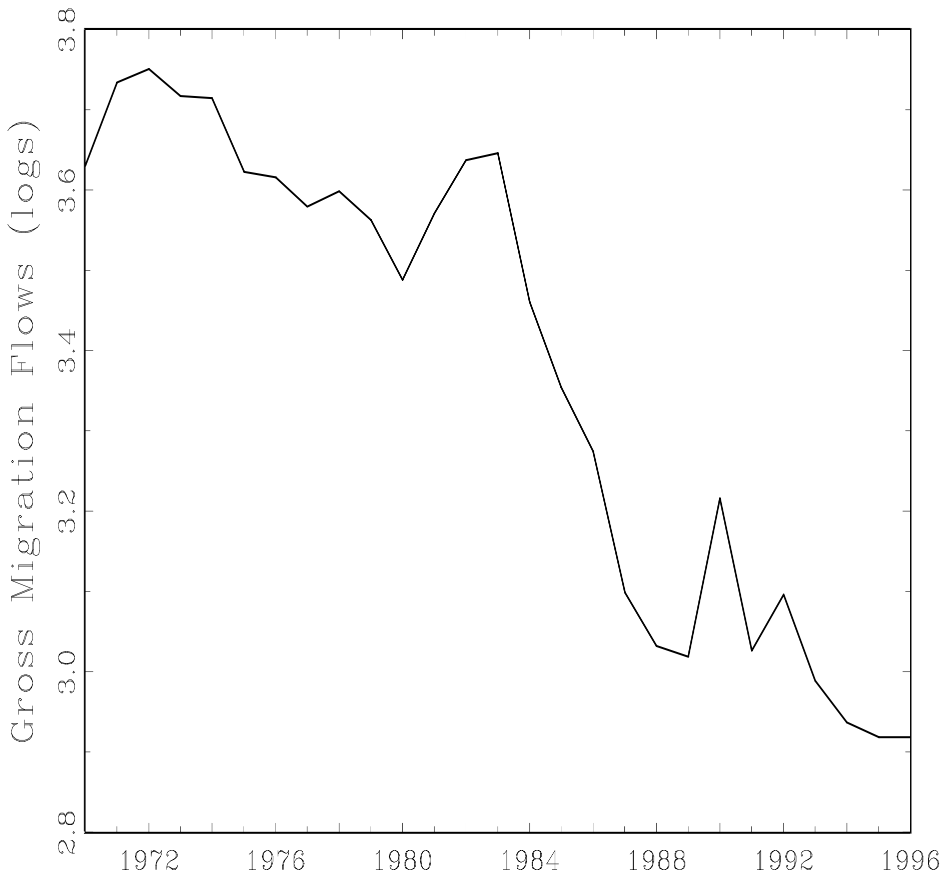

Fig. 1 Total gross migration flows from South Italy to Centre-North Italy, 1970-1998.

[4]According to the estimates reported by Bollino and Magnani (1997), between 1970 and 1992 GDP per head was on the average 58.5% and disposable income about 61.5% of those in the Centre-North. The North-South gap in disposable income was actually marginally larger in 1992 than in 1970 (respectively, 39.2% and 38.8%).

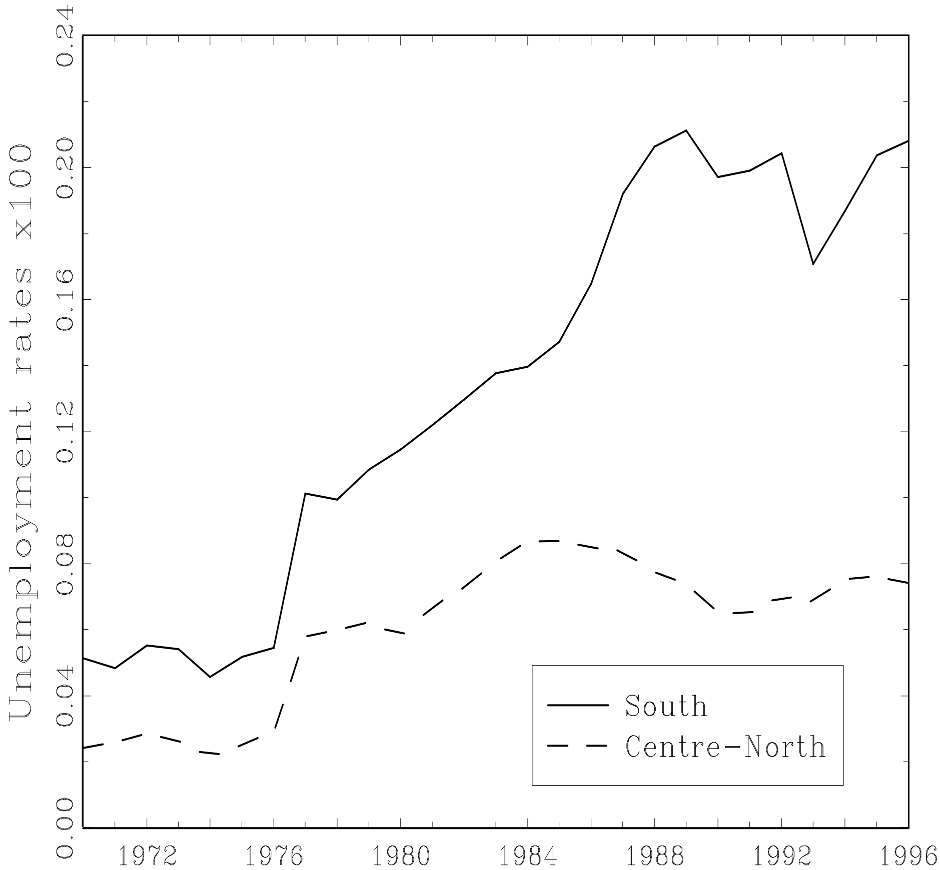

Fig. 2 Unemployment in South and Centre-North Italy.

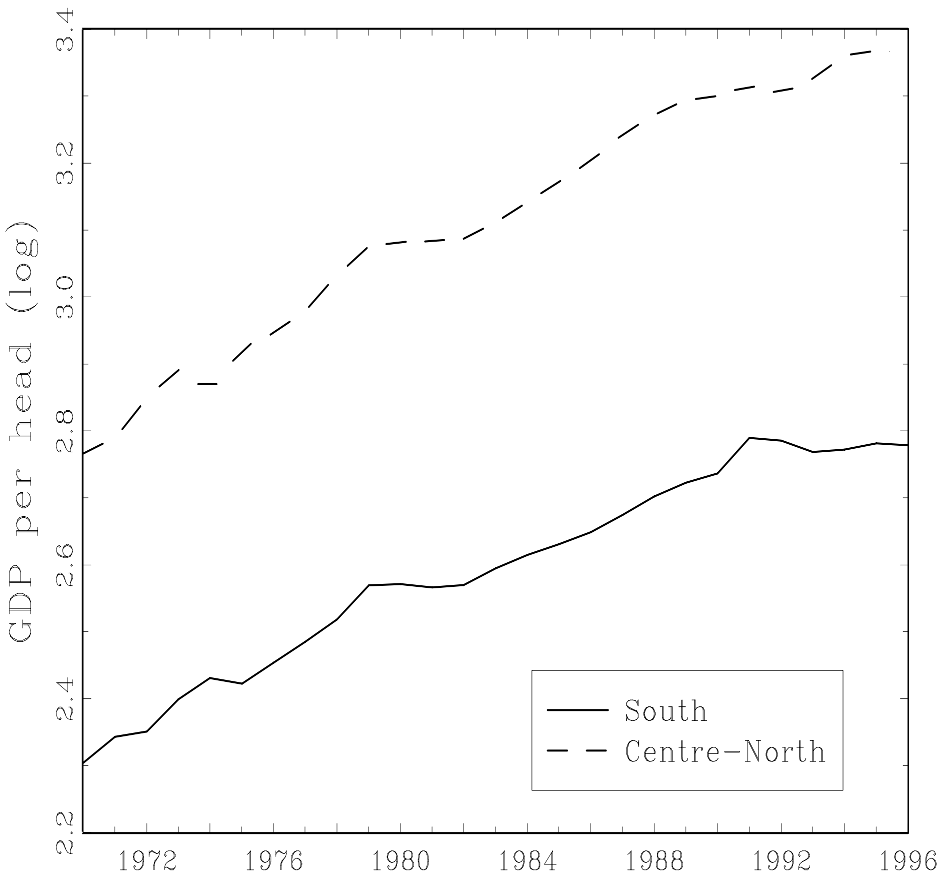

Fig. 3 GDP per head in South and Centre-North Italy

Summing up, we are apparently presented with an empirical puzzle: falling migrations with growing or at most constant regional disparities[5]. Obviously, there have been several attempts to explain this puzzle. Attanasio and Padoa-Schioppa (1991) emphasise the importance of the growth in disposable income, which, enabling the families to provide more support than in the past to unemployed members, reduced the incentive to migrate for given expected income differentials. Faini *et al.* (1997) and Cannari *et al.* (2000) take a broadly similar approach, stressing the inefficiencies in the job-matching process and mobility costs. Finally, Daveri and Faini (1999) stress risk factors, in practice measured by variables such as GDP variance and employment structure in the home region and correlation between GDP in the home and the destination region. Though these contributions may

[5]It is interesting to note that a similar puzzle seems to be present in the Czech Republic (Fidrmuc and Huber, 2003)

be varied and seemingly exhaustive, not taking into account the evident non-stationary of the data (which, as we will see below, is generally of a stochastic nature) they all share a serious methodological weakness. Their empirical results are thus open to criticism. In fact, this objection applies to the vast majority of the empirical literature on migrations: the issue of non-stationarity seems to be largely ignored even in the most recent contributions (*inter alia*, Mayda, 2004, Hatton, 2003, Hatton and Tani, 2003, Clark *et al.,* 2002); to the best of our knowledge, the only exceptions are Hatton (1995) and Brücker *et al.* (2003). The latter apply a panel cointegration test, thus taking correctly into account the non-stationarity issue and exploiting the panel structure of the data. However, the problem of dependence across units is ignored, so the approach is not entirely satisfactory. Thus, the objective of this paper is twofold. First, we are interested in examining the long-run determinants of internal migrations originating from regions in South Italy over a period spanning from the early 1970s to the late 1990s using a panel cointegration approach. However, as we will see in more detail below, no existing technique is suitable for carrying out this task. Hence, in order to accomplish it we will need to develop a bootstrap test for panel cointegration analysis with dependent units. Representing an advance with respect to both the existing migration literature and the methods for the analysis of non-stationary panel data, the empirical objective of the paper is hence a case study of hopefully general interest.

The structure of the paper is the following: we shall first discuss the Italian data and recall the theoretical model at the basis of the analysis (Section 2), then outline the bootstrap test and evaluate its properties by simulation (Section 3), present the empirical results (Section 4), and finally draw some conclusions (Section 5).

2 Modelling internal migrations: data and models

The main source for migration data in Italy are the records in the *comuni* (wards[6]) Registrars' Offices. As all data derived from administrative surveys, these data are not free from problems, above all the suspicion of a significant time lag between the actual migration and its registration (Cannari *et al.*, 2000). However, all Italian residents are required by law to register in the ward where they actually live and work, and, further, the registration is needed in order to have full access to the National Health System and state schools and pay lower council taxes: we may then expect most of the migration flows to be actually recorded. This data source presents also some distinct advantages: first of all, it does provide direct evidence on migration

[6]According to the Eurostat classification, Local Administrative Units (LAU) level 2, formerly NUTS (Nomenclature of Territorial Units for Statistics) level 4.

flows, as opposed for instance to the migration attitudes measured in the Labour Force Survey used by Faini *et al.*, (1997); second, the data are available by gender and with a very detailed geographic and age distribution. Let us consider initially the latter. Population structure is obviously a key determinant of migration. Adult migration rates are well-known[7] to decline with age, and this pattern is often mirrored within the younger age cohorts as well: very young children, generally dependents of young parents, tend to have higher migration rates than teenagers, whose older parents are less mobile. The resulting picture is confirmed in our case (see Fig. 4) and it is in fact obvious if, following standard models of migrations[8], we assume the incentive to move to be essentially given by the lifetime income differential, *i.e.* the present value of the stream of total future net income differentials. The important implication of this shape is that the elasticity of migrations with respect to variables such as regional income and unemployment differentials will depend on age: younger people react more strongly to any change because their time horizon is longer. Thus, in order to avoid aggregation problems fixed weights should be used in the aggregation process (Theil, 1954), and the usual mean migration rate defined as migrants/population, equivalent to the weighted arithmetic average of the migration rates of the various age cohorts with weights given by the (time-varying) shares of each age cohort, is not suitable. One possibility is to use as fixed weights either the shares at same specific time period (*e.g.*, the middle of the sample) or the averages over the entire period of interest. Although fixed for a given sample, weights of this type will however still be sample-dependent, so, any change in the sample will either lead to using totally arbitrary weights or force to recalculate the entire series. Fortunately, looking at Fig. 4 suggests a very simple solution to this problem, as the curves for the different years have very similar shapes though different means. Now, if the migration rates for the various age cohorts are approximately constant with respect to their (simple) mean, as indeed it seems to be the case, any weighted average with fixed-weights is obviously proportional to the simple mean, which can then be sued with no loss of generality. We shall thus measure the probability of migration by the arithmetic average[9] of the migration rates for the five-years age cohorts from to 0-5 to over 80, henceforth refereed to as the *standardised migration rate.*

[7]So much so that the "migrations" entry in the *Encyclopedia of Statistical Sciences (*Cox, 1985), includes a plot of migrations according to age described as "based on general experience" rather than on an actual data set.

[8]The seminal papers are Sjastad (1962) and Harris and Todaro (1970); for a survey, see *e.g.*, Ghatak *et al.*, (1996).

[9]Using the geometric average would have granted the interesting property that the log-linear aggregate model is the result of the linear aggregation of the log models for the individual age groups; however, extremely low, or even zero, migration rates are frequent in the older groups, and thus this option could not be considered.

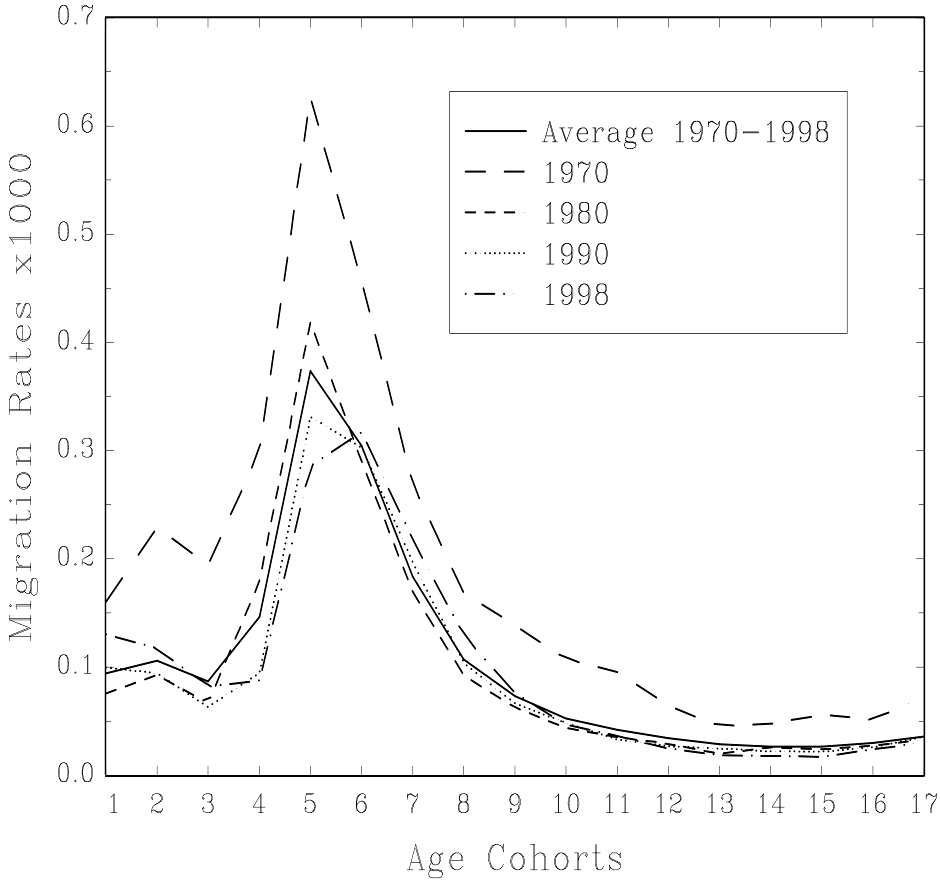

Fig. 4 Migrations rates ×1000 from South Italy to Centre-North Italy. Five-years age cohorts from 0-5 (label 1 on the x-axis) to 80 and over (label 17).

Let us now discuss the choice of regional disaggregation. A popular choice for regional studies of the Italian economy (see *e.g.*, Paci and Pigliaru, 1997) is the partition into the twenty NUTS 2 areas (*regions)*, eight of which are in the South. However, in our case this will involve modelling an exceedingly large total of $8 \times 12 = 96$ origin-destination pairs. Following approximately the NUTS 1 partition, we can instead identify seven groups of regions (descriptive statistics are reported in Table 1, and a map in Fig. 5) which seem more suitable for our purposes:

1. *North-West (NW)*: Piemonte, Val d'Aosta and Lombardia. Traditionally the most developed area of the country, but somehow stagnating in the 1980s and 1990s.

2. *North-East/Alps (NE/Alps)*: Trentino-Alto Adige and Friuli-Venezia Giulia. Both these regions are low-unemployment, affluent and fast-growing, and include mostly mountainous terrains (respectively 100% and 57% of the surface is officially classified as such).

3. *North-East/Po Valley (NE/Po)*: Veneto and Emilia-Romagna. From the economic point of view these two regions are very similar to the North-East Alpine regions, but they include mostly plains (respectively, 68% and 61% of the surface is officially classified as such), hence the urban structure is different.

4. *Centre*: Umbria, Marche, Toscana. In this area unemployment rates and income per capita are closer to the national averages, thus respectively higher and lower than in the North.

5. *Lazio*: this is the region where Rome, the nation capital and largest city, is located. Although geographically part of the Centre, its peculiar economic and social features suggest to treat it as a separate area[10]. First of all, the employment share of the non-market services sector is very high (on the average over the period of interest about 26% according to the ESA 79/SNA 68 definition, with a slightly growing trend), in fact much higher than both in the neighbouring regions of the Centre and in the entire nation (in both cases about 16%, with a slightly growing trend as well). Second, because of the massive immigration flows absorbed by Rome from the early '50s until the mid-70s (well over one million people: the population, 1.651.000 at the 1951 Census, had grown to 2.840.000 in 1981) we can expect so-called *migration chain* effects, which will be discussed in more detail below, to be particularly important.

6. *South-East* (SE): Abruzzo, Molise and Puglia. These are backward regions, with unemployment rates and income per capita respectively higher and lower than national average. Still, they are all better off than the other Southern regions[11].

7. *South-West* (SW): Campania, Basilicata, Calabria, Sicilia and Sardegna. The most depressed regions of the nation, with the highest unemployment rates and the lowest income per capita.

[10] This approach followed for instance by Eurostat in the definition of the regional aggregates used in the European Community Household Panel (ECHP) questionnaire (Eurostat, 2003)

[11] Attanasio and Padoa-Schioppa (1991) point out as a further difference that organised crime, with the associated negative esternalities, seems to be less important in the South-East than in the South-West.

Table 1
Income and Unemployment in the Italian Regions, 1970-96

	1970-77	1978-1991	1992-96
	GDP per capita		
North-West	18.1	24.6	29.1
North-East/Alps	16.3	23.5	28.8
North-East/Po Valley	16.7	23.8	29.3
Centre	15.7	21.4	24.9
Lazio	16.4	22.4	26.4
South-East	11.4	15.3	17.6
South-West	10.8	13.8	15.6
Italy	15.1	20.2	23.7
	Unemployment rate		
North-West	2.0	6.6	6.9
North-East/Alps	2.3	6.1	5.5
North-East/Po Valley	2.6	6.6	5.6
Centre	2.9	8.1	8.0
Lazio	4.3	10.3	11.3
South-East	4.6	12.0	14.2
South-West	5.4	16.8	21.5
Italy	3.8	9.5	11.2

GDP: Million of 1990 Lire (1936.27 Lire = 1 Euro);
Unemployment: $\times 100$; breaks in the series in 1977 and 1991;
Sources:
GDP: www.crenos.it (Paci and Pigliaru, 1997);
Unemployment: Istat, *Rilevazione delle Forze di Lavoro.*

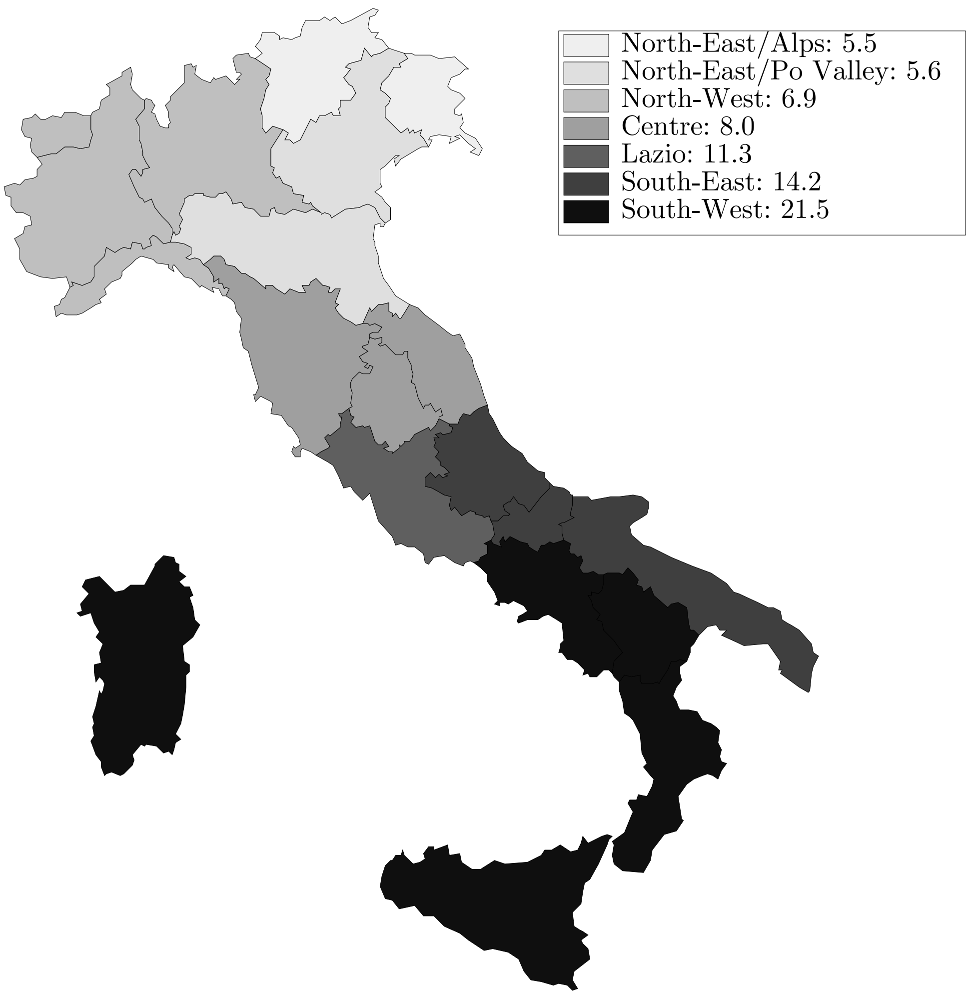

Fig. 5 Unemployment in the Italian regions in 1996 (%)

Having chosen these regional groupings we have two alternatives, as we can either consider flows between groups or flows from regions to groups. Under the former alternative we will obviously have six different cases when either the South-East and the South-West groups are taken as origins, while in the latter we will have $18 = 3 \times 6$ cases for migrations from the three regions of the South-East and $30 = 5 \times 6$ cases for those from the five regions of the South-West.

Finally, the gender issue: since the data are disaggregated by gender, we have the full range of options. Here the key point is that the female participation rate in the South, traditionally low, has been growing over the period under study: for instance, for the 25-40 cohort from about 35% in 1977[12] to over 50% in 1996. Given that the migration behaviour of individuals in and out of the labour force is likely to be different, in order to avoid serious aggregation problems we decided to concentrate the analysis on males, whose participation rates are high and stable (for the same age group and years, only a marginal decline from 96% to 91%). We also considered excluding the youngest and oldest cohorts (which are out of the Labour Force by definition), but, given that their contribution to the average migration rate is almost negligible (see Fig. 1), eventually we decided to include all cohorts in order to have a measure as close as possible to the commonly employed mean migration rate to facilitate comparisons with other studies.

As mentioned above, according to standard models the key determinant of migrations is the expected income differential, which, assuming for simplicity static expectations, is a function of current unemployment and income differentials. Short of measures of labour or disposable income at the regional level, we will use log GDP per capita; this will force us to choose 1996 as the end of the study period, as long regional accounts data are currently available only in the ESA 79/SNA 68 standard for the period 1970-1996. Since the small sample available suggests a cointegration analysis based on a single-equation method, we choose a set of explanatory variables not mutually cointegrated. Fortunately, unemployment and income differentials will be cointegrated if, and only if, unemployment and GDP in the origin and the destination areas are cointegrated with exactly the same coefficients, an extremely unlikely event which we can safely rule out. In order to capture structural push factors we will include in our model the log GDP per capita in the home region as well, so to capture the growth in the ability to support the unemployed population[13]. Another potentially relevant push factor is the share of agricultural employment in the home region, used by Daveri and Faini (1999). Workers employed in agriculture may have a higher propensity to migrate because their income is typically lower and more uncertain. The first effect is obviously captured by GDP per capita, while the second is not. However, there are two objections to the inclusion of this variable: the first is that it is likely to be endogenous with respect to migration flows; the second, entirely empirical, is that its corre-

[12] As mentioned above, the Labour Force Survey data before this year are not comparable for a break in the series.

[13] Faini and Venturini (1993) show that the relationship between home income and migrations may in fact be non-linear: positive at very low income levels, when income increases provide more means to finance migrations, then negative at higher income levels. Here we assume income to be always higher than the threshold separating the two regimes, so that the expected elasticity is negative.

lation with GDP per capita is so high (over 95% in both the South-West and the South-East) that including both variables causes severe numerical problems in the estimation. We thus included only the income variable. Finally, we will need a measure of the *migration chain* effect mentioned above. Migrants are known to move with a higher probability to destinations where people from the same area have moved to in the past, as it is easier to both obtain information on these destinations and to receive material support when settling down. This effect is often captured by including a lagged dependent variable (for instance, in Cannari *et al.*, 2000), which may help modelling short-run dynamics but is far from satisfactory when trying to estimate long-run patterns. Considering that the probability of accessing information and support is proportional to that of a contact with a past migrant, we can define two alternative measures of the migration chain effect. The total (males and females) migration flows from the home area to the destination area of interest in the previous years can be divided by either (i) the number of perspective migrants, i.e. in our case the male population in the home area, or, (ii), the total population, males and females. In the first case we are essentially estimating the probability of a direct contact, while in the second case we are allowing for indirect contacts by means of a female relative or friend, which every male in the population can be reasonably assumed to be in close contact with. Exploratory analysis showed that the results of the analysis are very robust with respect to both use of option (i) or (ii) and the number of years considered. These, however, cannot be very high given the length of the time series available; we thus settled for the previous three years.

Summing up, the measure of the propensity to migrate from home area h to the destination area i is $m_{hit} = \Omega^{-1}\sum_{x=1}^{\Omega} m_{xhit}$, with $m_{xhit} = Pop_{xht}^{-1}M_{xhit}$ the migration rate from h to i for age cohort x and $\Omega = 17$; the "migration chain" variable is $c_{hit} = Pop_{ht}^{-1}\sum_{s=1}^{3} M_{hit-s}$, where M_{hit} is the total migration flow from h to i and Pop_{ht} total population in the home area, at time t; finally, the log differentials between h and i are defined as $x_{hit}^{d} = \ln(x_{ht}) - \ln(x_{it}),\ \ x = y, u$, with the symbols y and u indicate, as usual, log GDP per capita and unemployment rate. The starting model for our empirical analysis is then the following:

$$m_{hit} = \beta_0 + \beta_1 y_{hit}^{d} + \beta_2 u_{hit}^{d} + \beta_3 y_{ht} + \beta_4 c_{hit} + \varepsilon_{hit}, \tag{1}$$

where h =home=South-East, South-West, i = destination=North-West, North-East/Alps, North-East/Po Valley, Centre, Lazio, South-East, South-West, with clearly $h \neq i$; $t = 1973, \ldots$,1996, as some initial observations are needed to compute the migration chain variable. We thus have only 24 time periods, and the power of any cointegration test must be expected to be very low. Fortunately, the set-up seems to lend itself naturally to a panel cointegration analysis, as for any given home area we can think of the six possible destinations as the "units". However, two problems arise: first of all, given the peculiar nature of our "units" (origin-destination pairs with a common origin) we must expect very high correlation in the errors across units; second, and far worse, one variable, log GDP per capita, is the same for all units. We thus have an extreme case of long-run dependence across units. Ignoring short-run cross-correlation and, above all, cross-units long-run dependence is known to cause severe size distortion (evidence is given respectively by O'Connell, 1998, Maddala and Wu, 1999, and Banerjee *et al.*, 2004), so that the power gain delivered by the panel dimension, which is the very reason for its use, is entirely fictitious. Although several panel unit root testing procedures allowing for heterogeneity and cross-section dependence of fairly general form have been recently proposed (Chang, 2002[14] and 2004, Moon and Perron, 2004, Phillips and Sul, 2003, Pesaran, 2005), progress under this respect seems to be much slower in the case of cointegration tests. The methods based on full system estimation (Groen and Kleinbergen, 2003, Larrson *et al.*, 2001) are in principle the most natural solution, but, as the number of nuisance parameters to be estimated grows with the square of the cross-section dimension, their empirical relevance tends to be limited to panels with a large number of time observations and a small number of units, a condition not met in our case. Within the class of single-equation methods very much the same applies to the GLS approach (O'Connell, 1998, Pedroni, 1997) which, furthermore, allows only for time-invariant cross-correlation patterns. Finally, PANIC (Bai and Ng, 2004) is explicitly designed for "large T, large N" panels (the smallest information set in Bai and Ng's simulations is $T = 100$, $N = 40$) and thus cannot be considered either.

Summing up, no panel cointegration test for dependent units with small samples over time and small to medium sample sizes over the cross-section dimension seems to be available yet. Although Maddala and Wu (1999) had already advocated solutions based on the bootstrap, this very natural option is still largely unexplored: examples of applications to panel unit root tests are Chang (2004) and Smith *et al.* (2004).

In the next section we will thus propose a bootstrap panel cointegration procedure; given the need to develop a procedure suitable for small samples we will confine our attention to single-equation methods, and, within this class, to the Group t-statistic (Pedroni, 1999), the cointegration version of the popular panel unit root test by Im, Pesaran and Shin (2003), and to a robust between groups statistic, *i.e.* the median of the cointegration statistics of the individual units. This will not cause any loss of generality, as the method developed can be applied to any other single-equation test.

[14] On this paper, see the critical note by Im and Pesaran (2003).

3 A Bootstrap Panel Cointegration Test

3.1 Set-up

For the sake of simplicity let us assume that the object of the study is the analysis of the long-run properties of two non-stationary random variables X and Y, with information available for N different units (indexed by i) over a sample of T observations (indexed by t); we thus have a panel. Excluding for notational convenience the case of deterministic time trends, the hypothesis of a long-run relation between X_i and Y_i with full coefficient heterogeneity may be expressed as

$$y_{it} = \alpha_i + \beta_i x_{it} + u^y_{it}, i = 1, \ldots, N; t = 1, \ldots, T, \tag{2}$$

and tested by one of the many available procedures aimed at evaluating the properties of the residuals of (2). Let $x_{it} = x_{it-1} + u^x_{it}$ and $u_{it} = [u^x_{it} u^y_{it}]$; then, under the assumption $E(u_{it} u'_{js}) = 0 \; \forall \; i \neq j$ and $\forall \; t, s$, Pedroni (1999) showed that both standardised sums of individual statistics and statistics computed on the pooled residuals of the N equations, (respectively *group mean panel cointegration statistics* and *panel cointegration statistics in* Pedroni's terminology) are asymptotically normal. The null hypothesis is obviously in both cases that of a unit root in the residuals of (2) for each i, i.e. cointegration in no units; the alternative hypothesis deserves some discussion. Although the alternative hypothesis of all the individual statistics is cointegration, this does not necessarily entail that the alternative hypothesis of the group mean statistic is "cointegration in all units". In fact, Pedroni (2004) argues that the alternative hypothesis is essentially determined by the economic model being tested, rather than by the statistic. Assuming this implies a given cointegrating relationship, if, for some reason, the model requires support from *all* units in order not to be rejected, then the alternative hypothesis will be cointegration in all units. If, on the other hand, the model is not so demanding, then the panel alternative hypothesis is simply that cointegration holds in a reasonably large number of units. As we will see, the simulation results show that the tests are powerful against an alternative where only some of the units are cointegrated, so that tests with this type of alternative are feasible. On the other hand, this implies that considerable care should be exercised when H_1 is of the first type (cointegration in all units), as H_0 may be rejected when in fact H_1 is not true. However, when the units are essentially homogenous (for instance, large EU or OECD economies) they may be expected to have similar DGP's, even if the small sample realizations may not always reflect it. Hence, in these circumstances the alternative hypothesis H_1 :"cointegration in a large number of units" may be adopted as a small sample approximation to H_1 :"cointegration in all units".

In all cases, the critical point of the tests is the assumption of independence. If it is satisfied, simulation evidence (*e.g.* Banerjie *et al.*, 2001) shows that the performances of the tests are reasonably good. However, this is not likely to happen in practice. Short-run cross-correlation can be eliminated up to a considerable extent by time dummies common to all units (a standard practice in the modelling of panel data, equivalent to de-meaning under homogeneity of the regressors), and thus it is not really a problem; long-run dependence, which may be a structural feature of the data or of the model, as for instance in the case of equation (1), is a much more serious question.

3.2 The Bootstrap Algorithm

The key point of any bootstrap procedure is how to construct the pseudodata. Our proposal here is to apply the Continuous-Path Block Bootstrap (CBB) independently to the cross-sections of time-series of the X's, $\{X_1 X_2 \dots X_N\}_{t=1}^{T}$ and the Y's $\{Y_1 Y_2 \dots Y_N\}_{t=1}^{T}$. Developed by Paparoditis and Politis (2001), the CBB is a block resampling method designed to construct non-stationary pseudodata. The pseudo-series is obtained in two steps: first, a block bootstrap series is constructed integrating within each block the resampled first differences of a series known[15] to be non-stationary; second, the end points of the blocks are chained so to eliminate jumps between blocks (this implies that the pseudo-series are shorter than the original series, as one observation must be deleted when chaining two blocks). As the resampling is applied to the entire cross-section the pseudo-series will clearly preserve the cross-correlation structure of the non-stationary individual time series. On the other hand, the blocks are chosen independently for the $X's$ and the $Y's,$ so that the two pseudo-series are independent by design. This property is critical, as a bootstrap test requires resampling under the null hypothesis, which here is no cointegration. Neither properties (correlation across units and no cointegration across variables) will be necessarily satisfied by pseudo-series constructed using the sieve bootstrap, the standard resampling algorithm for time series. Further, applying the sieve bootstrap to a panel cointegration set-up with k variables would involve the task of fitting $k \times N$ AR models.

Denoting by G a between group statistic (which may be Pedroni's Group t-statistic, the median of the individual cointegration ADF's, or any other between groups cointegration statistic[16]), the proposed bootstrap procedure includes five simple steps:

1. compute the Group statistic $\widehat{G}$ for the data set under study, $\{X_1 X_2 \dots X_N, Y_1 Y_2 \dots Y_N\}_{t=1}^{T}$;
2. construct separately by CBB two sets of N pseudo-series,

[15]For a variant designed for non-stationarity testing see Paparoditis and Politis (2003)
[16]Recall however that pivotal statistics may lead to higher order improvements.

$\{X_1^* X_2^* \dots X_N^*\}_{t=1}^{T^*}$ and $\{Y_1^* Y_2^* \dots Y_N^*\}_{t=1}^{T^*}$;

3. compute the Group statistics G^* for the pseudo-data set, $\{X_1^* X_2^* \dots X_N^*, Y_1^* Y_2^* \dots Y_N^*\}_{t=1}^{T^*}$;

4. repeat steps (2) and (3) a large number (say, B) of times;

5. compute the boostrap significance level; assuming that the rejection region is the left tail of the distribution, $p^* = prop(G^* < \widehat{G})$.

Three remarks are in order:

(i) The procedure can be applied to any between groups statistic: the most obvious candidate is the mean of the cointegration statistics for the individual units, but robust statistics such as the median may also be used.

(ii) Unbalanced panels can also be naturally handled by the procedure, as the cointegration statistics for the individual units are computed separately. If some of the individual series are much shorter than the majority of the panel use of a robust statistic is advisable.

(iii) The choice of the block length is a critical point of the algorithm. We will not enter into the issue, which is still essentially open (a thorough discussion can be found in Paparoditis and Politis, 2003), and fix the block length at 10% of the sample size, a choice that delivered good results in Paparoditis and Politis (2003)'s simulations. This entails that the performances of the bootstrap test are likely to be somehow inferior to those that may be obtained from fine-tuning the block length.

3.3 Monte Carlo Experiment

3.3.1 Design

The main part of the Monte Carlo experiment is based on a panel extension of the classical Engle-Granger bivariate data generating process (DGP), adopted by *e.g.* Kao (1999). One experiment will be based on a DGP mimicking (1), with respect to number of variables, units and observations and common regressors. In all cases the correlation across units is obtained as a consequence of a common factor in the disturbances, as in Pesaran (2005). In the basic DGP we then have a cross-section of N pairs of T observations over time of two, possibly cointegrated, non-stationary random variables, X and Y, driven by shocks ($u^j, j = x, y$) which are the sum of an idiosyncratic component ($\epsilon^j, j = x, y$) and a stationary common factor ($f_t^j, j = x, y$);

the former generates the long-run path, while the latter produces short-run correlation across units. More precisely:

$$\begin{cases} x_{it} = (1 - a_1)^{-1}(a_1 u_{it}^y + u_{it}^x) \\ y_{it} = x_{it} + u_{it}^y \end{cases} \tag{3}$$

where possibly $x_i = x_j$ for some i, j, and

$$\begin{cases} u_{it}^x = \gamma_i^x f_t^x + \epsilon_{it}^x \\ u_{it}^y = \gamma_i^y f_t^y + \epsilon_{it}^y \end{cases} . \tag{4}$$

The coefficients $\gamma_i^x, j = x, y$, are the factor loadings and determine the strength of the short-run cross-correlation across units. The structure of the idiosyncratic component is:

$$\begin{cases} \epsilon_{it}^y = \phi_i \epsilon_{it-1}^y + e_{it}^y \\ \epsilon_{it}^x = \sum_j e_{it-1}^x \end{cases} \tag{5}$$

so that when $\phi_i = 1$ there is no cointegration between X_i and Y_i, while the closer ϕ_i is to zero the higher is the speed of adjustment to the long-run equilibrium in unit i. Given that our aim is comparing the performances of the tests based upon the asymptotic distributions and the bootstrap procedures, without much loss of generality in the power simulations we will consider only the case $\phi_i \sim Uniform(0.2, 0.4)$. Finally,

$$\begin{cases} e_{it}^y \sim N(0, \sigma_i^2) \\ e_{it}^x \sim N(0, \sigma_i^2) \end{cases} \tag{6}$$

with σ_i^2 drawn from a Uniform density defined over an interval centred on 1, so to allow for some heterogeneity across units; here without loss of generality we chose $[0.5, 1.5]$. Clearly, with such a set-up we cannot aim at a full factorial design: the amount of information produced will be exceedingly large. Rather, we will define a benchmark case as close to reality as possible, and then explore variations in a few relevant directions, thus considering the following seven cases:

1. *Benchmark*: $N = 10; T = 30; \gamma_i^x, \gamma_i^y \sim Uniform(-1, 6)$. Both the time and the cross-section dimensions are small, but the latter is much smaller than the former. This is consistent with the assumptions underlying the asymptotics of the test, which is thus examined under rather favourable conditions. In order to obtain results as widely relevant as possible the number of time observations is similar to that often available for international macroeconomic data sets with annual data; the number of cross-section units could appear small, but it is plausible if we take for instance the largest world or European economies, or the NUTS 2 areas within a single European economy. The cross-correlation (about 0.65 on the average) is substantial.

2. *Low cross-correlation*: as Benchmark, except $\gamma_i^x, \gamma_i^y \sim Uniform(0,2)$, so that the correlation across units is moderate (about 0.30 on the average, less than half than in the Benchmark case).

3. *Independent units*: as Benchmark, except $\gamma_i^x = \gamma_i^y = 0, \forall i$; in order to assess the performance of the bootstrap tests we clearly need to consider a case satisfying the assumptions underlying the asymptotic test.

4. *Common regressor*: as Benchmark, except $X_i = X_1$, $i = 2, \ldots, N$, so that we have perfect long-run dependence across units. In this case the asymptotic test is known to collapse.

5. *Large N* : as Benchmark, except the cross-section dimension. This case is designed to evaluate the effects of increasing the cross-section sample size, either by (a) disaggregating the available units, or (b) adding new units. Given that adding new units and disaggregating those available are the spatial analogues of respectively extending the time span and increasing the sampling frequency, these experiments will allow assessing if a spatial analogue of the Shiller-Perron (1985) result holds. If this is the case, adding units will deliver a larger power gain than moving to a finer disaggregation. In both alternatives the sample size (30) is identical for the time series and cross-section dimension, a condition known from Banerjee *et al.* (2001) to be troublesome for the asymptotic test.

6. *Large T* : as Benchmark, except $T = 100$; this can be considered a rather large sample size in the time dimension, and all methods should deliver good results.

7. *Small N, small T, multivariate regression*: in this case the DGP mimics model (1): $N = 6$, $T = 24$, four right-hand side variables, one of which common to all units.

In all these cases we assumed cointegration to hold or not in all units at the same time. To shed some light on the results that may be expected when there is cointegration in a large fraction of, but not all, the units, we considered one more case:

8. *Variable cointegrating rank*: $N = 10, 30$ *(*respectively as *Benchmark* and *Large N)* with cointegration in $0.8N$ units.

In all simulations the number of bootstrap redrawings has been fixed at 500 and that of Monte Carlo replications to 1000; a few pilot studies made clear that a higher number of either would not have added much in terms of precision, while increasing significantly the cost and time scale of the experiment. In all cases we fitted a panel regression including common time dummies, computed the individual cointegration ADF statistics selecting the lag length by t-tests (Ng and Perron, 1995), and finally computed the asymptotic and bootstrap p-values for the Group $t-$statistic (respectively, $G - t_A$ and $G - t_B$ in tables 2-10) as well as the bootstrap p-values for the median of the ADF's ($Me - t$ in the same tables). Note that given the number of regressors and specification of the deterministic kernel the mean and variance of the Group $t-$statistic are known constants, and are thus irrelevant for the bootstrap calculations: as a consequence, using the bootstrap the number of regressors can vary across units. The bootstrap p-values have been also computed applying the *fast double bootstrap* (FDB). In previous work (Omtzigt and Fachin, 2002) we found this procedure, proposed by Davidson and MacKinnon (2000) for correcting possible bias in the bootstrap estimates of the p-values, to be able to deliver significant improvements in the performances of bootstrap tests on cointegration coefficients. Since going into the details of the method is clearly beyond the scope of this paper, we shall just provide a basic intuition. The idea behind the *double bootstrap*, proposed by Beran (1988), is that of correcting the possible bias in the bootstrap procedure using a second bootstrap layer. For instance, in the case of a test the aim of the second-level application of the bootstrap would be to estimate, and thus correct for, the bias $(p_\alpha - \alpha)$, where p_α is the p-value of the α-level bootstrap test. Although the principle is certainly attractive, it is also very expensive, as it involves the construction of a bootstrap pseudo-population for each bootstrap redraw. It is thus impossible to evaluate by means of Monte Carlo experiments with the currently available computing power. On the contrary, Davidson and MacKinnon's FDB involves only one second level bootstrap redraw for each first level one. The computing time is thus of the same order of magnitude of the standard bootstrap, and Monte Carlo experiments feasible. The intuition is as follows. Consider a one-sided test: if the bootstrap estimate $p^* = prop(s^* > s)$ of true p-value of the test is distorted, a better estimate may obtained by replacing s with some $\widetilde{s}$ chosen so to counterbalance the distortion. If for instance $p^* > p$, we should use some $\widetilde{s} > s$. Considering that s is by definition the $p^* - th$ quantile of the distribution of the s^*'s, an obvious candidate for $\widetilde{s}$ is the same quantile of a *second-level* bootstrap distribution. If p^* is distorted upwards, such a quantile will tend to be larger than the true quantile s, and viceversa, thus delivering the desired effect. Davidson and MacKinnon (2000) proposed two variants of the procedure, "FDB Type 1" and " FDB Type 2"; Type 1 is the preferred option, with Type 2 (which can be negative) suggested essentially as a reliability check. In our simulations the results delivered by Type 1 have always been confirmed by Type 2, hence not reported to save some space. Details are available on request.

3.3.2 Monte Carlo Experiment: Results

The results are reported in a separate table for each case, starting with the Benchmark in Table 2. Here we notice how with substantial cross-correlation the common time dummies are not sufficient to filter out all the dependence, so that using the asymptotic p-values leads to significant overrejection. On the other hand, the bootstrap procedures always have Type I errors close to nominal and power acceptable when tests are performed with nominal sizes greater than 5%[17]; considering that a 10% bootstrap test has a Type I error actually smaller than an asymptotic 1% test this is clearly not a problem. Use of the asymptotic test seems instead acceptable (provided common time dummies are meaningful in the model of interest and can thus be included: see the discussion in section 4) when the short-run dependence is moderate: From Table 3 we can see that with cross-correlation about 0.30 the asymptotic test has essentially no size distortion. The power of the two procedures is comparable for significance levels greater than 5%. To conclude the analysis of the various degrees of short-run dependence, from Table 4 we can note that if the units are independent the two tests show very much the same performances.

From the discussion above we know that long-run dependence is actually a much more serious problem than the short-run one. If the regressor is the same in all units (an extreme case of long-run dependence), the asymptotic test produces indeed disastrous results as expected, while those of the bootstrap tests are essentially comparable to the benchmark case (Table 5). The large T (Table 6) and large N (Tables 7 and 8) results are also very interesting. While a hundred observations over time are not enough for the asymptotic procedure to achieve Type I errors close to nominal size in presence of substantial short-run dependence across ten units, all the bootstrap tests are very close to this objective while at the same time delivering a power performance essentially equal to that of the asymptotic tests. When the number of units and time observations is the same, namely 30, we find, consistently with Banerjee *et. al.*, that the asymptotic tests overrejects heavily: in fact, Pedroni's results are based on the so-called sequential asymptotics, with T diverging for a fixed N prior to the summation over units. Increasing the number of units has, on the opposite, a beneficial effect on the performance of the bootstrap test: Type I errors are always close to the nominal sizes, and power is considerably higher both when the data are disaggregated and new units are added, with no significant difference between the two cases. For instance, the power of 5% bootstrap mean group tests ($G - t_B$) increases from 69% with $N = 10$ to over 90% in both cases with $N = 30$. Thus, disaggregating the units seems to deliver an informa-

[17]Although the large size distortions of the asymptotic test make power comparisons somehow difficult we prefer to report actual rejection rates, rather than size-adjusted power, as the former is the empirically relevant concept (Horowitz and Savin, 2000).

tion gain approximately equivalent to that given by new units. Since from Shiller and Perron (1985) we know that increasing the sampling frequency is not equivalent to extending the time span this result is somehow contrary to our expectations. One possible explanation may be that our DGP has no spatial structure: hence, the units produced by the disaggregation process are much more variable than consecutive observations in time usually are, and actually as variable as new units added to the sample. More work on this issue with a more realistic DGP allowing for correlation across units inversely related to distance is on our research agenda.

In a case similar to our empirical set-up (a multivariate model with information scarce both on the time and the cross-section dimensions, short-run dependence across units and a common regressor), the results (Table 9) are disappointing to say the least, as the bootstrap test has inadequate power while the asymptotic test is much less powerful than in the benchmark case, with an even slightly higher size distortion[18]. Hence, in a set-up of this type non-rejections of the bootstrap test should be regarded with caution, and more reliable results seeked by increasing the cross-section dimension.

Finally, the experiments with variable cointegration rank (Table 10) are also of same interest. We considered two cross-section dimensions, $N = 10$ and $N = 30$, with cointegration holding in 80% of the units. For all tests the probability of rejecting the null hypothesis, rather low with the smaller cross-section sample size, increases very fast so that with $N = 30$ it is essentially equal to that obtained with cointegration holding in all units; as far as the asymptotic test is concerned this is line with the findings reported by Gutierrez (2003). It is thus important to keep in mind that, consistently with Pedroni's (2004) view, rejection of the null of panel cointegration should not be taken as implying that cointegration holds in all units, but, rather, that is does in a reasonably large number of them.

Summing up, although the asymptotic test may be used under moderate short-run dependence provided common time dummies are included in the model, the bootstrap test, with no or very little size distortion (especially if Davidson and McKinnon's Fast Double Bootstrap is used) and comparable power under all circumstances, does appear to be superior. Further, the bootstrap allows any statistic of the individual ADF's, including robust statistics such as the median, to be used. This may prove important with unbalanced panels including much shorter series, hence potentially more subject to small sample bias, than the others.

[18] We did not include common time dummies, excluded in our empirical analysis; for a discussion, see section 4.

Table 2
Asymptotic and bootstrap cointegration tests
Case 1: Benchmark
$T = 30, N = 10$, strongly correlated units

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
A. H_0: $\phi_i = 1 \; \forall \; i$ true					
α	*rejection rates*				
0.01	0.11	0.01	0.01	0.00	0.01
0.05	0.20	0.03	0.02	0.03	0.02
0.10	0.26	0.07	0.05	0.08	0.05
0.20	0.34	0.17	0.12	0.16	0.12
B. H_0: $\phi_i = 1 \; \forall \; i$ false					
α	*rejection rates*				
0.01	0.90	0.34	0.28	0.36	0.29
0.05	0.95	0.66	0.54	0.63	0.53
0.10	0.97	0.79	0.69	0.77	0.67
0.20	0.98	0.90	0.84	0.88	0.81

Bootstrap: 500 redrawings, block size $0.10T$;
$G - t_A$: *Group t* asymptotic test;
$G - t_B$: *Group t* bootstrap test;
$Me - t$: Median of the individual ADF tests;
simple: simple bootstrap;
FDB: Fast Double Bootstrap Type 1.
The simulations for panel B are obtained with $\phi_i \sim Uniform(0.2, 0.4) \; \forall \; i$.

Table 3
Asymptotic and bootstrap cointegration tests
Case 2: Low correlation
$T = 30, N = 10$, weakly correlated units

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
A. H_0: $\phi_i = 1 \; \forall \; i$ true					
α	*rejection rates*				
0.01	0.02	0.01	0.01	0.00	0.01
0.05	0.06	0.03	0.04	0.04	0.05
0.10	0.08	0.08	0.09	0.09	0.09
0.20	0.15	0.19	0.17	0.20	0.19
B. H_0: $\phi_i = 1 \; \forall \; i$ false					
α	*rejection rates*				
0.01	0.96	0.87	0.80	0.83	0.77
0.05	0.98	0.96	0.95	0.95	0.93
0.10	0.99	0.98	0.97	0.97	0.96
0.20	1.00	1.00	0.99	0.99	0.98

all symbols and abbreviations: see Table 2

Table 4
Asymptotic and bootstrap cointegration tests
Case 3: Independent Units
$T = 30, N = 10$, Independent units

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
A. H_0: $\phi_i = 1 \; \forall \; i$ true					
α	*rejection rates*				
0.01	0.00	0.03	0.01	0.01	0.01
0.05	0.01	0.03	0.04	0.04	0.05
0.10	0.02	0.07	0.09	0.06	0.09
0.20	0.04	0.15	0.18	0.17	0.20
B. H_0: $\phi_i = 1 \; \forall \; i$ false					
α	*rejection rates*				
0.01	0.97	0.92	0.90	0.90	0.88
0.05	0.99	0.98	0.98	0.97	0.97
0.10	0.99	0.99	0.99	0.99	0.99
0.20	1.00	1.00	1.00	0.99	0.99

all symbols and abbreviations: see Table 2

Table 5
Asymptotic and bootstrap cointegration tests
Case 4: Common Regressor
$T = 30$, $N = 10$, correlated units, $X_i = X_1 \; \forall \; i$

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
		A. H_0: $\phi_i = 1 \; \forall \; i$ true			
α		*rejection rates*			
0.01	0.39	0.02	0.02	0.02	0.03
0.05	0.50	0.11	0.10	0.12	0.11
0.10	0.57	0.21	0.18	0.19	0.17
0.20	0.64	0.36	0.31	0.33	0.29
		B. H_0: $\phi_i = 1 \; \forall \; i$ false			
α		*rejection rates*			
0.01	0.95	0.56	0.43	0.56	0.44
0.05	0.97	0.80	0.71	0.78	0.71
0.10	0.98	0.88	0.81	0.85	0.80
0.20	0.98	0.95	0.90	0.91	0.88

all symbols and abbreviations: see Table 2

Table 6
Asymptotic and bootstrap cointegration tests
Case 5: Large T
$T = 100, N = 10$, correlated units

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
		A. H_0: $\phi_i = 1 \; \forall \; i$ true			
α		*rejection rates*			
0.01	0.06	0.01	0.01	0.01	0.04
0.05	0.11	0.04	0.05	0.03	0.04
0.10	0.16	0.09	0.09	0.07	0.08
0.20	0.21	0.21	0.19	0.19	0.19
		B. H_0: $\phi_i = 1 \; \forall \; i$ false			
α		*rejection rates*			
0.01	1.00	1.00	0.65	0.98	0.66
0.05	1.00	1.00	0.70	1.00	0.70
0.10	1.00	1.00	0.70	1.00	0.70
0.20	1.00	1.00	0.80	1.00	0.90

all symbols and abbreviations: see Table 2

Table 7
Asymptotic and bootstrap cointegration tests
Case 6a: Large N − disaggregation
$T = 30, N = 30$, strongly correlated units

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
A. H_0: $\phi_i = 1 \; \forall \; i$ true					
α	*rejection rates*				
0.01	0.53	0.01	0.01	0.01	0.01
0.05	0.66	0.07	0.05	0.08	0.06
0.10	0.71	0.17	0.12	0.15	0.13
0.20	0.77	0.37	0.27	0.31	0.22
B. H_0: $\phi_i = 1 \; \forall \; i$ false					
α	*rejection rates*				
0.01	0.99	0.59	0.48	0.59	0.49
0.05	1.00	0.90	0.79	0.86	0.77
0.10	1.00	0.96	0.90	0.93	0.87
0.20	1.00	0.99	0.97	0.97	0.94

all symbols and abbreviations: see Table 2

Table 8
Asymptotic and bootstrap cointegration tests
Case 6b: Large N − new units
$T = 30, N = 30$, strongly correlated units

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
A. H_0: $\phi_i = 1 \; \forall \; i$ true					
α	*rejection rates*				
0.01	0.45	0.01	0.01	0.01	0.01
0.05	0.57	0.07	0.05	0.06	0.03
0.10	0.63	0.13	0.10	0.15	0.10
0.20	0.69	0.29	0.23	0.28	0.23
B. H_0: $\phi_i = 1 \; \forall \; i$ false					
α	*rejection rates*				
0.01	0.99	0.63	0.50	0.65	0.52
0.05	1.00	0.87	0.78	0.87	0.79
0.10	1.00	0.94	0.89	0.92	0.89
0.20	1.00	0.99	0.96	0.96	0.94

all symbols and abbreviations: see Table 2

Table 9
Asymptotic and bootstrap cointegration tests
Case 7:
Small N, small T, multivariate regression
$N = 6$, $T = 24$, stronlgy correlated units,
one common regressor

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
		A. H_0: $\phi_i = 1\ \forall\ i$ true			
α		*rejection rates*			
0.01	0.13	0.00	0.01	0.00	0.01
0.05	0.26	0.04	0.04	0.06	0.06
0.10	0.34	0.07	0.07	0.12	0.10
0.20	0.42	0.18	0.15	0.21	0.18
		B. H_0: $\phi_i = 1\ \forall\ i$ false			
α		*rejection rates*			
0.01	0.39	0.07	0.09	0.08	0.08
0.05	0.52	0.20	0.20	0.22	0.21
0.10	0.59	0.32	0.30	0.34	0.31
0.20	0.70	0.48	0.45	0.52	0.50

all symbols and abbreviations: see Table 2;
block size: 3.

Table 10
Asymptotic and bootstrap cointegration tests
Case 8: Variable cointegrating rank
$T = 30$, strongly correlated units

	$G - t_A$	$G - t_B$		$Me - t$	
		simple	*FDB*	*simple*	*FDB*
		rejection rates			
α	$N = 10$, H_0: $\phi_i = 1\ \forall\ i$ false for $i \leq 8$				
0.01	0.77	0.21	0.17	0.23	0.18
0.05	0.83	0.49	0.40	0.51	0.41
0.10	0.85	0.64	0.54	0.64	0.55
0.20	0.88	0.77	0.70	0.76	0.69
	$N = 30$, H_0: $\phi_i = 1\ \forall\ i$ false for $i \leq 24$				
0.01	0.98	0.41	0.31	0.45	0.36
0.05	1.00	0.73	0.61	0.75	0.63
0.10	1.00	0.87	0.77	0.86	0.78
0.20	1.00	0.96	0.91	0.93	0.89

all symbols and abbreviations: see Table 2

4 Modelling internal migrations: empirical results

The results of the simulation study reported in the previous section suggest that, provided some care is exercised, the proposed bootstrap panel cointegration test may be used for an analysis based on our data-set and model. Given that South-West (SW) and South-East (SE) Italy, though both depressed areas, are not entirely homogenous, our aim is to investigate separately the long-run trends of migrations from these two areas. Partitioning the destination regions into the various groups introduced in Section 2 we will have six possible destinations (NW, NE/Alps, NE/Po Valley, Centre, Lazio, SW or SE) for each origin, so that it will be possible to examine the single equations carefully . Unfortunately, with $N = 6$ the panel cointegration tests must be expected to have very low power (see Table 9). On the other hand, considering as origins the individual regions within the SW (five regions) and the SE (three regions) and as destinations the six groups will increase significantly the sample size to respectively $N = 3$ origins $\times$ 6 destinations = 18 and $N = 5$ origins $\times$ 6 destinations = 30, but will make it more difficult to go into the details of individual cases. Trying to strike a balance between the opposite requirements of high power and careful analysis of individual cases, we shall first run the analysis with a partition of the destinations into groups of regions, and increase the sample size in the cross-section dimension by considering as origins the individual regions only if the hypothesis of no cointegration is not rejected.

As usual, as a first step we examined by ADF unit root tests the univariate properties of the series over the sample used for empirical modelling, hence excluding the observations used for initialising the migration chain. The order of the deterministic kernel has been determined following Ayat and Burridge's (2000) sequential procedure, thus including a trend when significant (which happened to be the case for almost all the tests). In the case of the log differentials trend stationarity (TS) may arise if either the two series involved also are trend stationary but the slopes are different, or if they are I(1) with different drift terms and cointegrate with a unit coefficient. Overall, the results of the ADF tests (reported in Table 11) are largely in favour of the hypothesis of difference stationarity. At the 1% level this is rejected in favour of the TS alternative only in the case of the log GDP per capita differential between the South-East and the North-West; in a few more cases it is rejected at 5%, always in favour of the TS alternative. This is particularly plausible in the case of South-West/South-East case, where the unit root hypothesis is rejected at 5% for all variables. For the migration rate the $I(1)$ hypothesis is rejected rather strongly (ADF statistic only slightly larger than the 1% critical point) in the case of the migrations from the South-East towards the Centre, while when the destination is the North-East/Po valley the evidence is marginal at 5%.

Table 11

ADF Unit Root Tests, 1973 – 1996

	South-West			
y	-2.04^{C}			
	u^d	y^d	c	m
NW	-3.30^{T}	-3.95^{T*}	-1.93^{T}	-3.03^{C}
NE/Alps	-1.13^{C}	-3.00^{T}	-3.03^{T}	-3.44^{T}
NE/Po	-2.76^{T}	-2.54^{T}	-3.78^{T*}	-2.40^{T}
Centre	-2.78^{T}	-2.60^{T}	-2.79^{T}	-3.06^{T}
Lazio	-2.92^{T}	-2.91^{T}	-3.02^{T}	-3.44^{T}
SE	-4.18^{T*}	-3.65^{T*}	-4.31^{T*}	-3.79^{T*}
	South-East			
y	-1.86^{T}			
	u^d	y^d	c	m
NW	-2.27^{C}	-5.34^{T**}	-1.78^{T}	-3.13^{T}
NE/Alps	-1.37^{C}	-2.46^{T}	-1.83^{T}	-2.49^{C}
NE/Po	-2.79^{T}	-1.79^{T}	-2.95^{T}	-3.92^{T*}
Centre	-3.63^{T*}	-2.10^{C}	-2.07^{C}	-4.29^{T*}
Lazio	-1.50^{C}	-2.47^{T}	-4.12^{T*}	-3.29^{T}
SW	-4.18^{T*}	-3.65^{T*}	-3.07^{T}	-1.82^{T}

y : GDP per capita; u^d : log unemployment differential;
y^d : log unemployment differential;
c : migration chain; m: standardised migration rate;
^{C}: Constant included; ^{T} : Constant and Trend included;
*: significant at 5%; **: significant at 1%;
Lag selection: 10% t-test on coefficient of last lag, max lag = 3.

Before moving to the estimation phase we need to consider a preliminary issue. As mentioned above, common time dummies are often included in panel studies; for instance, in this context by Daveri and Faini (1999). The practice of including these type of dummies derives from the "small T, large N" panel regression literature, where most of the variance is across units, and shocks occurring over time to all units are indeed sheer noise which should be filtered out. The welcome side effect of reducing the dependence across units made this practice standard in the non stationary panel literature based on asymptotic unit roots or panel cointegration tests as well. However, the role played by common time dummies when the time dimension is substantial deserves to be examined carefully. For instance, looking at Fig. 6 it is clear that in the case of a panel regression with dependent variable the migration rates from the South-West, the dummies approximate a mostly downward-sloping deterministic segmented trend. As the ADF tests suggest that the standardised migration rate is generally difference stationary, there is no reason to include such a trend in our model: hence, we will base our analysis on equations without time dummies. Note that this implies that our estimates will not be comparable with those obtained by Daveri and Faini (1999), as in this case the role of the explanatory variables is simply to explain the deviations of the dependent variable from the segmented deterministic trend.

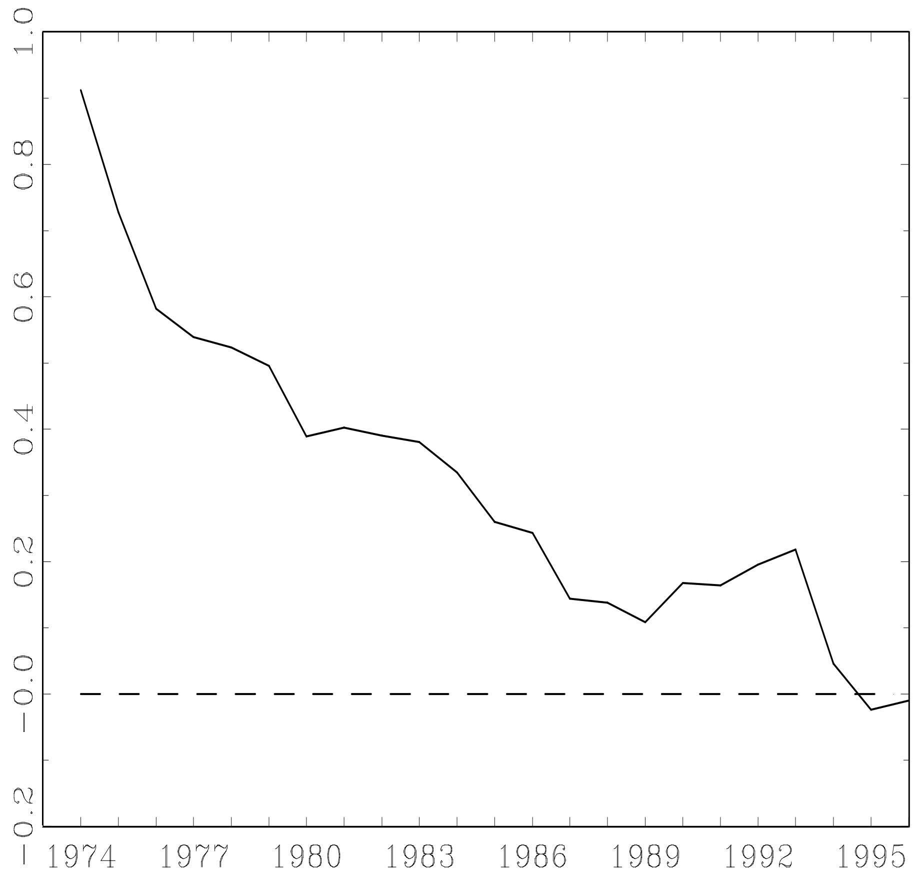

Fig. 6 Panel OLS regression for migrations from the South-West: coefficients of the common time dummies.

Let us start with the South-West. On the basis of the ADF tests we excluded from the panel of the destinations the South-East, as in this case all variables seem to be trend stationary; in the equation for the North-West we excluded the GDP differential, also trend stationary. The results of panel cointegration tests with fully heterogenous specification (fixed effects, heterogenous slopes), are reported in the top panel of Table 12, and FM-OLS estimates of the individual equations in the bottom part of the same table. The bootstrap algorithm used 1000 redrawings and block length fixed at 3; some experiments showed the results to be rather robust to the choice of the latter within a reasonable range. The p-values for the $Group\ t$ and $Median\ t$ statistics are all smaller or only slightly larger than 5%, thus supporting the view that the models specified are cointegrating relationships. However, if we examine the estimates of the cointegrating coefficients obtained by FM-

OLS in unit-by-unit regressions[19] (equivalent to a panel regression without time dummies and with heterogenous coefficients) we can discover that some coefficients are not significant according to asymptotic inference on the t-values, and, further, in some cases the income differential, though significant, has a positive effect. Thus, an income growth in the home area relatively to destination areas would *increase* the propensity to migrate: a clearly spurious relationship.

Table 12
Modelling Males Migration Rates, 1973-96
Home Area: South-West - Unrestricted models

Panel Cointegration Tests		Bootstrap p-values $\times 100$		
		simple	FDB_1	FDB_2
Group t	-3.66	4.0	5.5	5.4
Median t	-4.49	3.2	4.1	3.8

FM-OLS estimates

Destination	θ	u^d	y^d	y	c	Z_α
North-West	2.25 [2.69]	0.51 [7.86]	–	-1.14 [4.12]	0.08 [0.45]	-15.35
North-East/Alps	2.18 [4.30]	0.24 [8.64]	0.40 [1.92]	-1.24 [6.33]	-0.21 [6.33]	-16.65
North-East/Po	-0.54 [1.54]	0.34 [7.14]	-1.96 [6.57]	-0.74 [4.22]	–	-18.53
Centre	2.10 [2.53]	–	2.65 [4.52]	-0.56 [1.96]	-0.17 [0.88]	-23.34
Lazio	1.12 [1.10]	0.19 [1.21]	3.06 [3.42]	-0.81 [1.98]	0.16 [0.87]	-23.31

Bootstrap: 1000 redrawings, block length: 3;
FDB: Fast Double Bootstrap, type 1 and 2;
θ : constant;
u^d : log unemployment differential (home-destination);
y^d : log GDP per capita differential (home-destination);
y : log GDP per capita in home area;
c : migration chain;
$t-$statistics: in brackets; $-$: TS variable not included;
Z_α: Phillips' cointegration test; 10% critical value: -23.5

We will tackle this problem in two alternative ways: since the bootstrap allows different specifications across units (this is not possible when using the asymptotic procedure, as the correction factors are tabulated for a fixed number of variables), one option will be to repeat the entire analysis (panel cointegration testing and estimation) eliminating the variables with wrongly-signed coefficients as well as those with non significant t-tests

[19]Individual units cointegration tests are also reported; except two cases, the statistics are rather distant from the rejection region.

from the model . The second option, which we will examine first, will involve keeping the specification fixed, and replacing FM-OLS with the Pooled Mean Group (PMG) estimator put forth by Pesaran *et al.* (1999). This method is designed to estimate autoregressive-distributed lags (ARDL) panel equations with completely heterogenous short-run dynamics and partly or entirely homogenous long-run coefficients. Although somehow limited by the assumption of independence across units, in our case it is an alternative worth considering to FM-OLS estimation[20]: the FM-OLS estimates suggest that the homogeneity restriction is plausible for the log GDP in the home region, closely linked to the GDP per capita log differential. Thus, following this alternative estimation strategy may help in solving the problem of the coefficients with wrong signs.

Setting the initial values of the long-run coefficients as equal to the Mean Group estimates and selecting the lag order of the ARDL on the basis of the Schwarz criterion, with a maximum lag set to 2, we obtain reasonably well-specified equations (Table 13). The diagnostics (serial correlation, heteroskedasticity, Normality and functional form) are never significant except one case (functional form, 5%); the fit is fairly or very good (0.60 to nearly 0.90) for three equations, though rather poor (about 0.40) in two; finally, the adjustment coefficient (ϕ) is always large, confirming that the specified equations are cointegrating relationships. The coefficients of the log unemployment differentials tend to agree fairly closely with the FM-OLS estimates, while those of the GDP per capita differentials now have always the expected sign and are generally larger in absolute value than the FM-OLS estimates. This is also the case for the pooled estimate of the coefficient of log GDP per capita in the home region, which, as signalled by the Hausman statistic, is identical to the average of the heterogenous estimates.

[20]Another promising alternative, which will be the subject of future research, is Pesaran's (2004) "Common Correlated Effect" estimator. This method extends to panel estimation Pesaran's (2005) principle of augmenting the equations with cross-section averages in order to deal with dependence across units. Its properties are very good in stationary panels, but yet unknown in non-stationary ones.

Table 13
Modelling Males Migration Rates, 1973-96
Home Area: South-West - PMG estimates

	Destination				
	NW	NE/Alps	NE/Po	Centre	Lazio
ϕ	-0.42 [2.95]	-0.46 [4.14]	-1.00 [*n.a.*]	-2.67 [10.08]	-1.00 [*n.a.*]
θ	0.94 [0.64]	1.46 [3.45]	0.86 [3.80]	10.62 [8.77]	0.10 [0.66]
y^d	-4.33 [1.29]	-0.21 [0.28]	-3.87 [13.02]	-2.05 [12.16]	-0.72 [4.53]
u^d	0.59 [2.79]	0.24 [2.03]	0.44 [10.24]	0.30 [9.48]	2.39 [3.07]
c	-0.05 [0.12]	-0.73 [2.92]	-0.59 [5.55]	-0.94 [13.16]	2.27 [6.25]
y	-2.10 [17.61]				
$\overline{R}^2$	0.60	0.40	0.80	0.86	0.38
$\widehat{\sigma}$	0.07	0.07	0.05	0.06	0.07
LL	32.50	32.70	43.17	37.90	32.54
SC	0.00	0.00	0.41	3.20	1.16
FF	2.21	1.37	0.24	0.69	4.86*
NO	0.77	0.44	0.39	1.31	2.02
HE	0.14	0.07	1.39	0.29	0.15
Hausman	0.00 [1.00]				

ϕ : error correction coefficient;
LL : Log-likelihhod;
SC: Serial Correlation statistic, $\chi^2(4)$;
FF: Functional Form statistic, $\chi^2(1)$;
NO: Normality statistic, $\chi^2(2)$;
HE: Heteroskedasticity statistic, $\chi^2(1)$;
all other abbreviations: see Table 12;
in brackets: *coefficients*, t-statistics; *Hausman*, p-value.

Let us now go back to the our initial estimation and testing strategy, namely panel cointegration ADF testing associated with FM-OLS estimation of the individual equations. The results obtained after eliminating the variables with non-significant or wrongly-signed coefficients are reported in Table 14. The cointegration p-values are generally much below 10% and, especially in the case of the *Group t* statistic, only marginally higher than those obtained with the full specification. Recalling that with the sample size at hand power must be expected to be low we can conclude that the hypothesis of no cointegration is strongly rejected; all the variables included in the final specification are strongly significant and have the expected sign. The plots of the series and FM-OLS estimates (Fig. 7) show that the models manage to capture the main trends as well as some local swings, as *e.g.,* in the last part of the sample in the case of the migrations towards the North-West. Home income is definitely the most important explanatory variable: it enters all equations but one, with elasticity on the average slightly larger than unity in absolute value (-1.02). The income differential enters only in the equation for North-East/Po Valley, with a very large elasticity; this is also somehow consistent with the PMG results, as in this case the point estimate of elasticity in the North-West equation is slightly larger in absolute value than that in the North-East/Po Valley equation, but has a much larger variance. The unemployment differential enters all the equations for migrations towards the Northern areas, but with rather small coefficients (0.34 on the average; recall that the PMG estimates are also rather small for this variable). Finally, the migration chain measure is relevant only for the migrations towards the two central areas, Centre and Lazio. The former result was expected and the latter, given the lower relevance of pull factors (the regions in the Centre have lower per capita income and higher unemployment than those in the North), is also reasonable. Summing up, applying two different estimation methods (FM-OLS and PMG) we obtain consistent evidence of weak effects of unemployment: this is in line with previous results stressing the weakness of the link between migrations and unemployment in Italy *(* Cannari *et al.* 2000) and other European economies *(* for instance, for the UK economy Pissarides and Mc Master, 1990, McCormick, 1997). The evidence on income effects is mixed, with the level of home income appearing more important than relative income differentials. Thus, our results lend strong support to Attanasio and Padoa-Schioppa (1991) who, on the basis of descriptive evidence, identified the growth of income in the Southern regions as the main cause of the falling trend in migrations. In our own analysis income differential seems to matter most for migration towards the North-East/Po valley area, indeed where GDP per head grew fastest over the period of study (see Table 1).

Table 14
Modelling Migration Rates, 1973-96
Home Area: South-West - Restricted Models

Panel Cointegration Tests		Bootstrap $p-values \times 100$		
		simple	FDB_1	FDB_2
Group t	-2.59	5.4	7.8	7.3
Median t	-3.68	7.7	10.6	8.9

FM-OLS estimates

Destination	θ	u^d	y^d	y	c	Z_α
North-West	2.03 [4.06]	0.51 [5.09]		-1.03 [4.91]		-9.16
North-East/Alps	0.87 [1.87]	0.17 [2.19]		-0.86 [4.37]		-13.09
North-East/Po	-0.54 [1.54]	0.34 [7.14]	-1.96 [6.57]	-0.74 [4.22]		-18.53
Centre	1.09 [7.04]				0.50 [2.84]	-6.77
Lazio	1.29 [1.24]			-1.47 [4.53]	0.40 [1.64]	-17.60

all symbols and abbreviations: see Table 12.

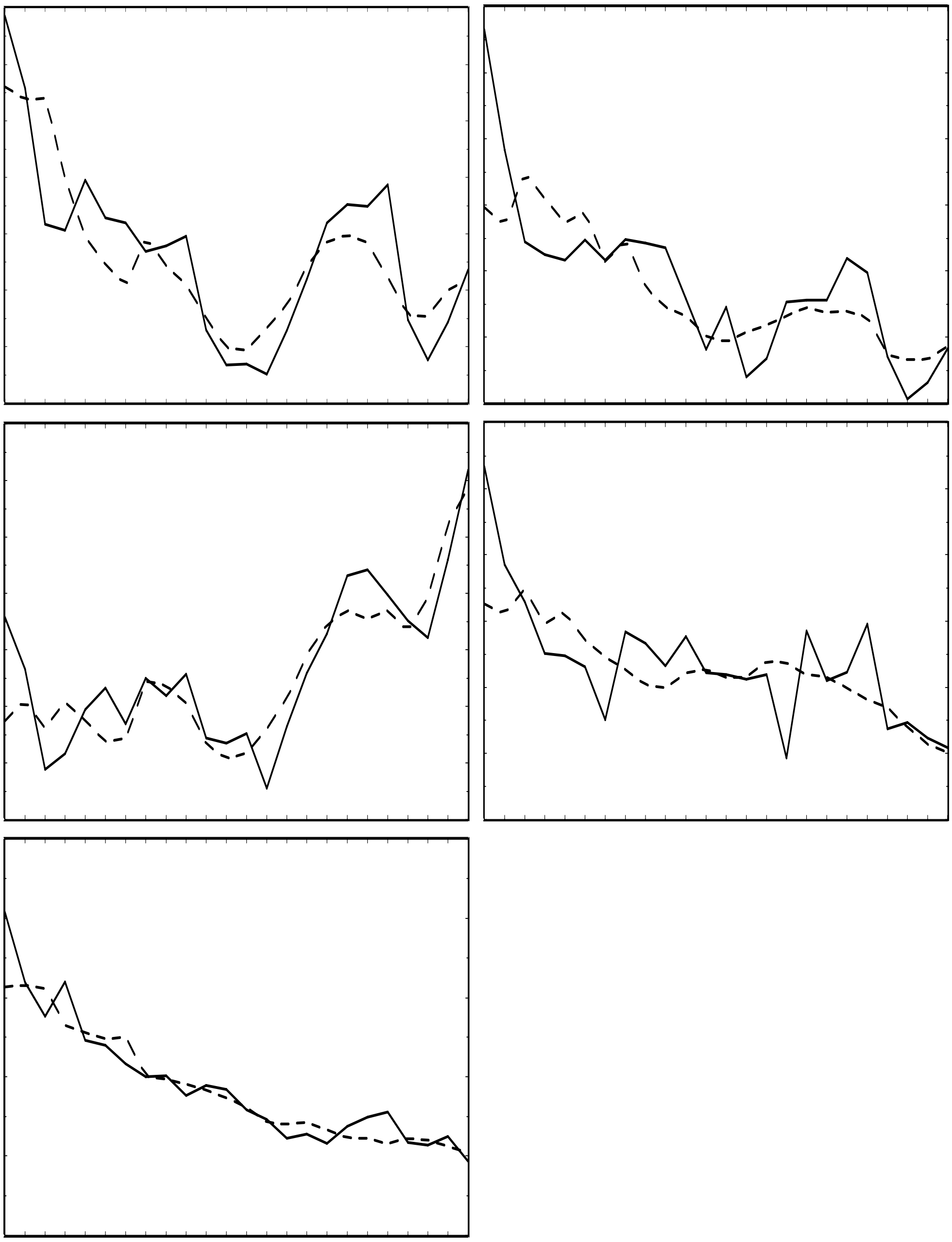

Fig. 7 South-West: Log Standardised Migration rates (solid line) and FM-OLS estimates (dashed line), 1973-96. From left to right and top to bottom: destination North-West, North-East/Alps, North-East/Po, Centre, Lazio.

In the case of migrations from the South-East we excluded from the panel the Centre but decided to include the North-East/Po valley, as the unit root hypothesis for the migration rate towards this destination would be rejected only marginally at 5%. We also excluded from the equations all explanatory variables trend stationary at 5%. In the first estimation round (Table 15) the hypothesis of no cointegration is never rejected, with $p-$values around 20% for the $Group - t$ statistic and 50% for the $Median\ t$. In this case as well some variables appear with a wrong sign, but unfortunately PGM, which assumes the existence of a long-run relation, it is not a viable option. We shall thus proceed by excluding the variables suspected to have a spurious relationship with the migration rate. This produces only partially the hoped results: with the restricted models the p-values are around 8% for the $Group\ t$ statistic, which could be considered satisfactory evidence for rejection given the sample size, but over 15% for the $Median\ t$ (the detailed results, not included to save space, are available on request). Given that this outcome may be a simple consequence of inadequate power we will replicate the analysis modelling migrations from each of the three regions of the South-East (from north to south along the cost of the Adriatic Sea Abruzzo, Molise and Puglia) to the five areas considered so far, thus increasing the sample size in the cross-section dimensions to $N = 15$. The increase in sample size apparently does not produce the desired effect, as with the unrestricted model the hypothesis of no cointegration is not rejected even more largely (p-values over 50%; see Table 16). However, a close inspection of the FM-OLS estimates reveals that a large proportion of the coefficients has wrong signs or is suspiciously small and very imprecisely estimated. Now, we should keep in mind that given the very small time sample size (24 observations) the coefficients of non-cointegrating variables have a non-negligible probability of being different from zero. If this is actually the case, even if a cointegrating relationship exists, the estimated residuals of the fitted equations will be the sum of a stationary component (the cointegrating combination) and a non stationary one (the non-cointegrating variables weighted with their non-zero coefficients), hence would appear as non-stationary. This suggests that single-equation cointegration tests with small samples should follow a sequential approach, starting with all bivariate models (H_0: $rank = 0$ against H_1: $rank = 1$) and then moving to the multivariate cases. For instance, consider a trivariate model with variables y, x_1 and x_2, where only the first two, y and x_1, form a cointegrating combination. The first step should be to test if (y, x_1) and (y, x_2) are cointegrating combinations; suppose the tests correctly suggest that (y, x_1) cointegrate, while (y, x_2) do not. The next step would be to test if (y, x_1, x_2) cointegrate. Although with a large sample size the coefficient of x_2 will converge to zero and the cointegrating combination (y, x_1) will be identified again, with a small sample size the coefficient of x_2 may be small but not enough, so that the test may fail to reject the hypothesis of no cointegration among these three variables. However, we already know from the results of the bivariate tests that (y, x_1) do cointegrate, and thus draw the correct conclusion that there is one cointegrating relationship, including y and x_1, but not x_2. Unfortunately, in a panel context this approach is unfeasible, as the number of cases to consider for k left-hand side variables and N units is $[\sum_{j=1}^{k} \binom{k}{j}]^N$. The sequential procedure would thus present delicate problems of size control and indeed overall control of the analysis, which in practice would need to be entirely automatic. The alternative option is starting from the most general specification and trying to identify possible non-cointegrating variables. Hints helping this search may be coefficients (i) with wrong signs and/or (ii) very small and imprecisely estimated; if the variables eliminated from the regressions indeed do not enter any cointegrating combination the p-values of the test for H_0 : no cointegration will fall with respect to the more general specification. Thus, although the selection of the variables to exclude is not based on a test, we do have a formal control $ex-post$. We followed this option, defining "very small and imprecisely estimated" as smaller than 0.10 in absolute value and with standard errors greater than the coefficient; in our case many coefficients are actually smaller than this threshold and much smaller than their standard errors. Confirming that the variables eliminated from the regressions according to this criterion are indeed not cointegrated with the migration rate, the $p-$values drop dramatically to below 1% (*Group t*) or just above it (*Median t*). The final results are reported in Table 17, with plots in Fig. 8; looking at the plots it can be appreciated how, as suggested by the strong agreement between the p-values for the *Group t* and the *Median t* tests, in the vast majority of cases the equations capture rather well both the long-run trends and some local swings. Inspection of the individual equations reveals that the specification is highly variable across units; hence, on the basis of this evidence PMG estimation is not advisable. In most cases the only retained variable is GDP per head in the home region, often with rather large elasticities, while income differential enters only two equations, with small elasticities. In line with previous findings, very much the same applies, except a couple of cases, to the unemployment differential. Finally, the migration chain effect matters in a few cases, sometimes with a negative sign. This is rather difficult to rationalize; a possible explanation may be that in cases where the labour market in the destination region was moving towards excess supply the incentive to migrate may be inversely related to the size of the migration flows in the recent past.

Table 15
Modelling Migration Rates, 1973-96
Home Area: South-East - Unrestricted Models

Panel Cointegration Tests		Bootstrap p-values $\times 100$ simple	FDB_1	FDB_2
Group t	-2.30	19.5	20.2	20.7
Median t	-3.54	46.9	52.7	52.4

FM-OLS estimates

Destination	θ	u^d	y^d	y	c	Z_α
North-West	3.95	0.08	–	-1.06	0.03	-7.57
North-East/Alps	3.70	0.25	-3.87	-2.04	-0.26	-14.43
North-East/Po	4.42	-0.01	-0.26	-1.51	-0.42	-11.96
Lazio	3.57	1.12	-3.58	-1.18	–	-9.14
South-West	6.19	–	–	-2.41	-0.73	-10.71

all symbols and abbreviations: see Table 12.

Table 16

Modelling Male Migration Rates, 1973-96

Home Area: South-Eastern Regions - Unrestricted Models

Panel Cointegration Tests		Bootstrap p-values $\times 100$		
		simple	FDB_1	FDB_2
$Group - t$	-2.69	43.1	58.7	58.4
$Median - t$	-3.47	67.0	82.0	92.0

FM-OLS estimates

Destination	θ	u^d	y^d	y	c	Z_α
			Origin: *Abruzzo*			
North-West	-1.85 [0.78]	-0.11 [0.61]	–	-0.96 [2.34]	-0.10 [0.25]	-21.84
North-East/Alps	-1.47 [1.47]	0.05 [0.08]	0.27 [5.03]	-0.56 [3.32]	0.12 [0.68]	-27.52
North-East/Po	-4.68 [3.83]	-0.28 [2.66]	0.11 [1.91]	-1.18 [6.10]	-0.66 [2.67]	-20.31
Lazio	-1.23 [1.95]	0.94 [4.32]	0.15 [1.35]	-0.36 [2.35]	–	-19.56
South-West	-8.88 [7.91]	–	–	1.57 [8.49]	-0.77 [3.83]	-11.25
			Origin: *Molise*			
North-West	-2.47 [4.51]	0.12 [2.96]	–	-0.96 [11.65]	-0.09 [0.75]	-21.68
North-East/Alps	-6.54 [6.38]	-0.16 [2.89]	0.08 [1.09]	-1.66 [10.4]	-0.80 [3.96]	-18.90
North-East/Po	1.39 [1.27]	0.17 [2.20]	0.14 [1.86]	-0.26 [1.52]	0.66 [2.80]	-16.10
Lazio	-0.96 [0.59]	-0.14 [0.37]	0.12 [0.69]	-0.10 [0.28]	–	-20.39
South-West	-8.26 [3.24]	–	–	-1.86 [4.71]	-0.44 [0.92]	-10.42
			Origin: *Puglia*			
North-West	-2.45 [1.05]	0.31 [2.40]		-0.70 [1.76]	0.40 [1.08]	-16.15
North-East/Alps	4.18 [1.25]	0.74 [4.28]	-0.28 [1.86]	0.58 [0.99]	1.20 [2.44]	-17.21
North-East/Po	8.10 [7.52]	-0.15 [2.31]	-0.02 [0.32]	-1.77 [9.22]	-0.82 [4.78]	-13.93
Lazio	-7.64 [14.60]	0.13 [1.76]	-0.09 [2.09]	-1.39 [11.47]	–	-10.05
South-West	-13.00 [4.04]	–	–	-2.83 [5.00]	-0.99 [2.22]	-11.66

all symbols and abbreviations: see Table 12.

Table 17
Modelling Male Migration Rates, 1973-96
Home Area: South-Eastern Regions - Restricted Models

Panel Cointegration Tests		Bootstrap p-values $\times 100$ simple	Bootstrap p-values $\times 100$ FDB_1	Bootstrap p-values $\times 100$ FDB_2
Group t	−6.33	0.2	0.0	0.2
Median t	−3.67	1.4	2.1	2.1

FM-OLS estimates (no time dummies)

Destination	θ	u^d	y^d	y	c	Z_α
			Origin: *Abruzzo*			
North-West	−1.23 [3.41]			−0.84 [9.48]		−18.37
North-East/Alps	−0.08 [0.05]			−0.33 [1.46]	0.36 [1.47]	−25.21
North-East/Po	−1.37 [2.56]			−0.65 [4.95]		−18.13
Lazio	−1.17 [1.70]	0.95 [4.03]		−0.35 [2.04]		−18.60
South-West	−8.88 [7.91]			−1.57 [8.49]	−0.77 [3.83]	−11.25
			Origin: *Molise*			
North-West	−2.80 [13.16]	0.10 [2.80]		−0.99 [20.66]		−9.10
North-East/Alps	−3.52 [5.98]			−1.30 [9.35]		−10.74
North-East/Po	3.13 [7.93]	0.17 [1.65]			0.99 [4.54]	−6.16
Lazio	−1.42 [1.58]			−0.20 [0.96]		−13.37
South-West	−6.23 [6.92]			−1.59 [7.47]		−3.75
			Origin: *Puglia*			
North-West	−4.88 [5.22]	0.26 [2.37]		−1.09 [5.19]		−9.05
North-East/Alps	0.57 [1.15]	0.71 [4.21]	−0.19 [1.23]		0.61 [2.14]	−16.30
North-East/Po	−7.18 [4.65]			−1.67 [6.14]	−0.54 [2.53]	−13.76
Lazio	−7.65 [14.60]	0.13 [1.76]	−0.09 [2.09]	−1.39 [11.47]		−10.05
South-West	−13.00 [4.04]			−2.83 [5.00]	−0.99 [2.22]	−11.66

all symbols and abbreviations: see Table 12.

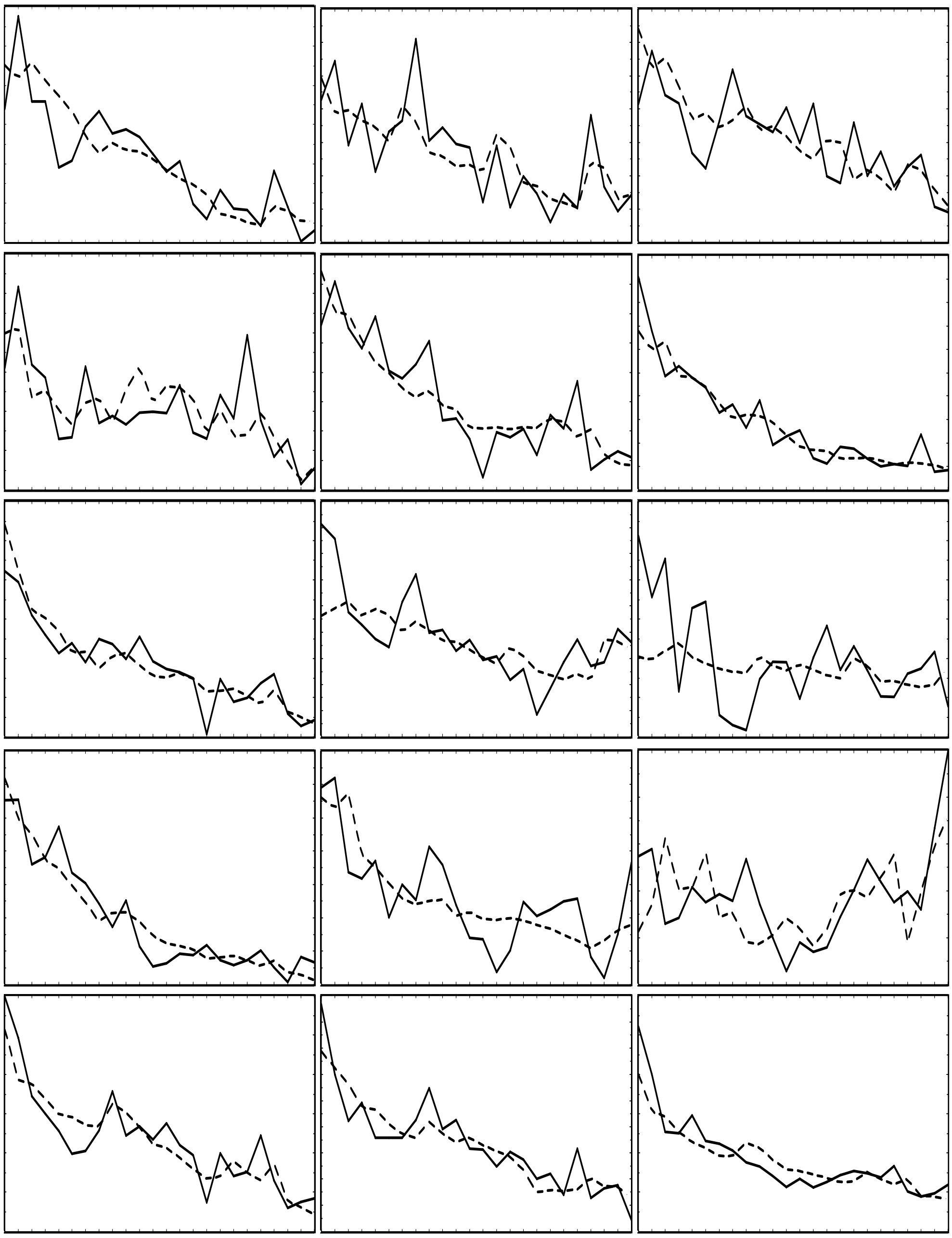

Fig. 8 South-Eastern Regions: Log Standardised Migration rates (solid line) and FM-OLS estimates (dashed line), 1973-96. Columns: from left to right, origin Abruzzo, Molise, Puglia; rows: from top to bottom, destination North-West, North-East/Alps, North-East/Po, Lazio, South-West.

5 Conclusions

The aim of this paper was to model internal migrations from South Italy over the last three decades, a period when the propensity to migrate fell dramatically in spite of mass unemployment and rising regional disparities. Previous attempts to explain this apparent puzzle failed to take into account the non stationary nature of the data involved, and are thus open to criticism. However, the annual frequency of the migration data implies that the sample sizes available are rather small, and thus a long-run study is not a trivial task. Although the set-up points quite naturally to a panel cointegration approach, here the problem is that we have short- and long-run dependence across units with small sample sizes over both time and cross-section dimensions. Hence, all asymptotic techniques currently available are not valid, because either independence across units (all single- equation panel cointegration tests, such as those proposed by Pedroni and Kao) or a large time sample size (*e.g.*, the ML and PANIC approaches) is required. We thus developed a bootstrap test of panel cointegration based on the Continuous-Path Block bootstrap; Monte Carlo evidence suggests that the proposed test is robust to both short- and long-run dependence across units and has good size and power properties. A particularly important one is that (contrary to asymptotic tests derived under the so-called sequential asymptotics assuming divergence of the dimension of the time sample prior to that of the cross-section sample) increasing the cross-section dimension with a fixed time sample produces an increase in power with Type I errors always close to nominal sizes.

The test has then been applied to long-run models of the propensity to migrate measured as the simple mean of age-specific migration rates, so to avoid the usually overlooked problem of aggregation and filter out the effect of changes in population structure. The empirical results obtained by either FM-OLS and PMG point to income growth in the sending region as the main factor explaining the decline in the migration rates, thus lending new support to Attanasio and Padoa-Schioppa's (1991) view that the key factor of the decline in internal migrations in Italy was the growth in the ability to support the unemployed population in the depressed regions. Income and unemployment differentials seem to play only a minor role, in the latter case consistently for instance with the evidence available for the UK economy (Pissarides and Mc Master, 1990, McCormick, 1997, Hatton and Tani, 2003).

6 References

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