Modelling Disaggregate and Aggregate Labour Demand Equations

Cointegration Analysis of a Labour Demand Function for the Main Sectors of the Italian Economy: 1950-1990

di

Barbara Pioresi

Dicembre 1993

Dipartimento di Economia Politica
Via Giardini 454
41100 Modena (Italia)
Modelling Disaggregate and Aggregate Labour Demand Equations

Cointegration Analysis of a Labour Demand Function for the Main Sectors of the Italian Economy

BARBARA PISTORESI *

J.E.L. C32, J23

Abstract: This paper tests for the existence of cointegration between employment, real wage and output both for the main sectors of Italian economy (agriculture, industry, services and public administration) and for the aggregate series. The Johansen (1988) estimation procedure is utilised on the period from 1950 to 1990. The tested macro cointegration is strong while the sectoral cointegration is weaker owing to the non-uniformity of the cointegration tests and to a cointegration residuals that are trended. Moreover the macro dynamics and the micro one are very different. Hence the macro cointegration does not seems to reflect the micro behaviours and seems to emerge as a spurious result of the aggregation process. This could be due to the presence of I(1) idiosyncratic components in the micro series that make the sectoral cointegration difficult, but nearly cancel out when the aggregation process is performed. The conclusion is that an aggregate Error Correction Model for the labour demand does not seem to have an empirical microbackground.

* Dipartimento di Economia Politica, Facolta'di Economia e Commercio, Universita'di Modena, Via Berengario 51 - Modena.
1. Introduction

In the last fifteen years the Italian economy, like the majority of the European countries, has experienced a steady increase in both employment and unemployment. The fact that the demand for labour has not increased enough to absorb the growing labour supply and to offset the increase in unemployment raises the following questions: which are the key-determinants that have prevented labour demand from increasing sufficiently? And which are the sectors that have determined the evolution of employment in Italy?

In this economic context there has been a proliferation of estimates of labour-demand functions both in a pure neoclassical specification in the relative prices (Jenkinson 1986, Lucifora 1987, Symons 1981, Symons and Layard 1984) and in a mixed specification in which output becomes a key determinant of the movement of employment (Beckerman and Jenkinson 1986, Briscoe and Wilson 1991, Chiarini and Placidi 1991, Layard and Nickell 1978, Modigliani, Rossi and Padoa-Schioppa 1986, Parigi and Urga 1993, Prosperetti and Urga 1989, Sargent 1978, Smith and Hagan 1993). In general, the first specification is derived in a framework of competitive market and the second in a context of imperfect competition. However, for different functional forms of the production function, both under monopolistic competition and perfect competition, it is possible to express marginal productivity of labour in terms of average productivity and hence of output level. Thus the mixed specification is compatible both with a market clearing hypothesis and with a disequilibrium hypothesis in which the representative firms can be constrained by demand or labour costs. A critical survey on the specification of the labour demand can be found in Zenezini (1992a, 1992b), while a different theoretical position is offered in Bodo and Gavosto (1992).

---

1 This is a substantially revised version of my MSc Dissertation presented at the Department of Economics of the Warwick University in September 1993. My thanks are due to my supervisor Jeremy Smith for constructive comments on the earlier draft. I am also grateful to Mario Forni and Marco Lippi for many helpful suggestions on the final version of this work and to Marcello D’Amato for several helpful discussions and criticisms. I have also received encouragement and some final advice from Luca Marinelli and Antonio Ribba. Errors or omissions the author's responsibility alone.
Both specifications have often been estimated by imposing *a priori* theoretical constraints about the determinants of the employment and on the structure of the adjustment that are rarely tested. On the contrary, cointegration analysis enables testing of the long run relationships implied by economic theory and lays the foundations for a correct dynamic analysis. The link between cointegration and dynamic specification is made thanks to the *Representation Theorem* (Granger 1981, Engle and Granger 1987): error correcting behaviour on the part of economic agents will induce co-integrating relationships among the corresponding time series and vice versa. In other words the variables in the error correction term in an ECM must be cointegrated and cointegrated variables must have an ECM representation.

This result leads to a re-evaluation of the econometric modelling based on the adjustment costs (Davidson et al. 1978, Hendry 1980, Hendry et al. 1980) that emphasises the use of an Error Correction Mechanism to achieve the short run consistency of an economic relation with the steady state equilibrium of the variables in it. One important result of this literature concerns the microfoundation of the Error Correction Models. Nickell (1985) and Salmon (1982) demonstrate how an Error Correction Model is consistent with optimising behaviour on the part of economic agents. This is also true for the labour demand derived as a two step maximisation problem of a firm that optimises a quadratic loss function to adequate the current employment to the optimal one (Nickell 1986). This micro result is in general tested at macro level under the assumption that agents are equal and that the information on the shape of the micro relationships can be transferred to the macro equation. If this were true we would be able to find at any aggregation level the same information as with the macro relationship.

In this work the data show that cointegration at disaggregate level is more difficult to accept than at aggregate level and hence macro cointegration does not seem to be the result of the maximising behaviour of a representative firm. In fact the cointegration at micro level reflects different firm behaviours in different sectors. Moreover, we will show that it is not possible to construct an ECM for the labour demand at a disaggregate level, whereas it is possible at an aggregate one. The result is derived by using multivariate cointegration analysis as in Johansen
We test the existence of cointegration among employment, output and product real wage in the main sectors of the Italian economy and at the aggregate level. Particular attention is paid to the weakly exogeneity tests on the estimated adjustment coefficients to the long run equilibrium in order to establish the existence of a dynamic labour demand equation with an ECM form.

While the specification used in this work is common for the analysis of the labour demand in industry, it is not so for the analysis in sectors such as agriculture or services, where the movements of employment could follow simpler schemes. In services, for example, the movements in employment could be related to the anti-cyclic adjustment, while in agriculture they could be negatively correlated to the movements of the extra-agricultural employment and to an autonomous exodus from this sector. Moreover, in public administration the labour input is not generally determined by an optimisation problem, but jobs are frequently created for political rather than economic reasons. However, we think that these simplifications can be neglected since the purpose of this work is not to seek for a better labour demand specification, but rather to offer an empirical contribution to the issue of aggregation.

The structure of the work is as follows. Section 2 discusses the data and the behaviour of the series. In Section 3 the order of integration of the series is determined through the tests of unit root: Dickey-Fuller tests and Phillips Perron tests. Section 4 outlines the method of estimation that is based on the multivariate cointegration procedure. The estimation of the cointegration space in each sector and some structural hypotheses of economic interest within this space are presented. Attention is paid to the inclusion of a time trend in the cointegration vectors in order to take into account the possibility of "stochastic cointegration" between the variables (Johansen 1991a, Johansen 1991b, Juselius 1991). In this section the comparison of macro and micro results is also performed while in Section 5 some theoretical results about aggregation and cointegration are presented. Moreover, an example is given in order to illustrate that micro cointegration may be more difficult than macro because of the presence of idiosyncratic components in the micro series. Section 6 concludes.
2. Data, behaviour of the series and variable definitions

In this work a new Italian data set (Rossi N, Sorgato A. and Toniolo G. 1992) is used. These annual data consist of a statistical reconstruction of the Italian accounts between 1890 and 1990 that is consistent with the revision of the national accounts recently undertaken by the Italian Statistical Office (ISTAT 1989). The data set contains the main supply and demand components of GNP, both at current and constant prices, an appraisal of capital stock, a reconstruction of the hours worked by fully-employed male equivalents (homogeneous labour units) in the private and public sector and the hourly wage rate at current prices, both gross and net of the social security contribution.

The series utilised are disaggregated into the main branches of the economy: agriculture (including forestry and fishing), industries (mining and quarrying, manufacturing, electricity gas and water, construction), services (trade, transport and communication, finance and insurance, miscellaneous services, housing) and public administration. For each of these sectors there are series for gross domestic product at constant (1985) factor prices as a measure of the output (demand), the deflator of GNP as an index of output price, the gross nominal wage and the gross real wage (producer wage) constructed as nominal wage over output price as a measure of the cost of labour for the firm, the total hours worked as employment. The capital formation and export series are not used because they are not disaggregated across sectors.

By using total hours worked instead of employment, we are implicitly assuming that both the variables have the same returns and the same "adjustment mechanism". The first assumption has been made quite extensively in the literature (for example, Dhrymes1969 and McCarthy 1975) even if there is some evidence of different elasticity with respect to output. A greater elasticity for the hours is normally estimated (Feldstein 1967). The second assumption is more restrictive: in fact in Italy there is a wide flexibility in adjusting the hours worked and high rigidity in employment because of the presence of organised unions and a more labour-protectionist legislation with respect to other European countries (Bodo 1984).
The period of estimation used in this analysis is from 1950 to 1990 as the employment series contains a lot of omitted observations for the period 1893 to 1910 and during the two world wars. All the variables are in logarithms.

On inspection, the first differences of all the variables seem to exhibit a non-zero drift. The long run trend for agricultural employment is downwards. This suggests that a redistribution of workers from the agricultural sector to non-agricultural activities happened in the period under consideration. This redistribution is attributable in particular to technological progress. The increase in productivity is due to the use of less labour and more fixed capital because of an increase in agricultural wages with respect to prices of machines, involving labour saving (Ricardian assumption). The price of machines is related to technological innovation in the industrial sector. It is important to note that the real wage in the agricultural sector increases very fast with respect to the other sectors, thus reducing the gap with the other wages (Fig.3). This fact could confirm the Ricardian substitution effect. Another reason for the negative trend in agricultural employment could be the increase in the labour demand in the other sectors due to the increase in relative outputs. The output growth in agriculture is substantially inferior to that in other sectors (Fig.6), in particular the change in agricultural employment is inversely correlated with industrial production. So the reduction in the agricultural labour supply may be due to the higher wages in the non agricultural sectors (Fig.3 and 4). Both the effects contribute to determine a marked exodus from the agricultural sector.

The basic trend in industrial employment is upward, but it tends to stabilise in the 1970s until the 1980s, when it becomes downward as in many European countries. Industrial employment varies over the cycle, with the movements of output. It shows more oscillation than the other employment series in accordance with the movements of the relative output (Fig.6, 7, 9, 10). In particular, in the 1980s the decrease in industrial employment could be due both to the decrease in the rate of growth of income and to the high real wages. Employment in the private-sector services has an upward trend with slope larger than that of the industrial sector, principally during the 1970s. In the 1980s when industrial employment is decreasing, employment in services
and public administration is once more increasing through less than in the 1970s (Fig.10). This phenomenon has been defined "dynamic transfer" between industry and services and probably is due to the increase in the services for industrial firms as indicated by Momigliano and Siniscalco (1982). Actually the series for services output jumps less than the series for industrial output in the early 1980s and the gap between industrial production and output in the services increases markedly throughout the 1980s (Fig.7). However, this phenomenon could also be explained by the influence of relative real wages. In fact, industrial real wages increase when employment is decreasing, while the stability of employment in services is accompanied by reduction in the relative real wages (Fig.3, 10).

The trend in public administration employment has been upward for a long time. During the post-war period public employment has grown by over 2% a year. through in recent years this trend has tended to slow down, probably because of the budget deficit. This positive trend is due, on the one hand, to the constant increase in the functions performed by the public sectors, while, on the other hand, increase in public employment may be due to political reasons.

The plots of the series utilised for this analysis are in the Appendix.

2.1 Variable definitions

- EA: agricultural employment, EI: industrial employment, ES: employment in services, EP: employment in public administration;
- YA: agricultural real output, YI: industrial real output, YS: real output in services, YP: real output in public administration;
- WRA: real wage in agriculture, WRI: real wage in industry, WRS: real wage in services, WRP: real wage in public administration;
- ET: total employment, YT: total output, W: representative real wage for the economy;
- L indicates the logarithm of the series and $\Delta$ is the differencing operator.
3. Integration analysis

The multivariate cointegration analysis performed by the Johansen procedure (Johansen 1988, 1991a) is based on the assumption that all the variables are integrated of order one. A series is integrated of order one if contains only one unit root. If some of the series in the system are integrated of a higher order than one, e.g. I(2), then a more complicated estimation procedure is required to analyse the problem (Johansen 1991b, 1992).

All the series utilised show an evident profile of non stationarity. So they could contain one or more unit roots. Consequently, the first step in the Johansen procedure is to test the order of integration of the variables. For this reason the Dickey-Fuller tests and the Phillips-Perron tests are conducted to verify the presence of unit roots.

The simple data generation process in which it is possible to test the presence of unit root is

\[ y_t = \alpha y_{t-1} + u_t \]

but if it is the series can be supposed to have a trend in the levels a more general specification must be adopted

\[ y_t = \mu + \alpha y_{t-1} + u_t \]

In general it is convenient to start with a general specification of the autoregressive process with also a trend

\[ y_t = \mu + \beta \tau + \alpha y_{t-1} + u_t \]

and testing down until a more parsimonious autoregressive specification is selected. The testing strategy adopted in this work is that proposed by Perron (1988). It consists of a sequence of t-
tests and F-tests\(^2\), starting with the model (3), and testing the presence of unit root separately from and jointly with the significance of the trend and the drift in the different models above. The distribution of these statistics is non-standard because of the presence of non-stationary series and the retabulated critical values are in Dickey-Fuller (1979, 1981) and in Mac Kinnon (1991).

The simple Dickey Fuller tests (t-test or F-test) are based on the assumption that the DGP is an AR(1). In some cases the DGP has a richer dynamics. In this situation the Dickey Fuller regression shows autocorrelated residuals and a more general specification is necessary. The Said-Dickey approach (Said and Dickey 1984) represents a generalisation of the Dickey Fuller procedure for testing the unit root and yields test statistics with the same critical values. The Said-Dickey tests (Augmented Dickey Fuller) add lagged changes \(\left(\sum y_{t-i}, i = 1, \ldots, k\right)\) in the dependent variable to avoid the autocorrelation.

Another alternative procedure is owing to Phillips and Perron (1988). This procedure modifies the statistics through a non-parametric correction of the covariance matrix of residuals, to take account of the autocorrelation (or heteroscedasticity). The critical values are the same as for the Dickey-Fuller tests. The "adjusted" DF-type statistics are denoted \(Z\)-statistics.

The main drawback in computing the \(Z\)-statistics is that of choosing the number of residuals autocovariances which are to be used in implementing the correction. The same problem arises in the choice of the lags in the ADF tests. In our case the computer program (Shazam\(^3\)) used to perform the tests automatically chooses the number of lags on the base of the Newey and West (1987) method. In some cases the automatic truncation lag does not seem to be appropriate, so in the tables of results we report both the automatic tests and the minimum number of lags: 1. In general one lag is enough to whiten the residuals and the results, in terms of either acceptance or rejection of the null hypothesis of unit root, are the same in the two choices. In some cases there is a contrast between the results from the Dickey-Fuller tests (DF and ADF) and the Phillips Perron tests in presence of non-normality of residuals. In these situations we

\(^2\)The \(t\)-tests are denoted in the tables by \(T_t\) and \(T_{\mu}\), while the F-tests are denoted by \(\Phi_3\), \(\Phi_2\) and \(\Phi_1\).

\(^3\)Shazam' Econometrics Computer Program, McGraw-Hill.
choose the Dickey-Fuller results, following Handa and Ma (1989). These authors argue that from Monte Carlo experiments it seems that in "small sample" and in presence of non normality of residuals the Dickey-Fuller tests have better properties.

The same testing strategy is conducted both for the Dickey Fuller type tests and the Phillips-type tests. When variables are in levels we start with the model (3) and test down to a more parsimonious model. The presence of unit root is tested at each different stage of the strategy. When variables are in differences model (2) is utilised. We report the Phillips-type tests even if the diagnostic test on the residuals from the Dickey Fuller regression does not show autocorrelation. In general the results in the two types of tests are compatible.

The results from the unit root tests are broadly consistent with the results obtained by an inspection of the plots. Both the disaggregated and the aggregated employment, output and real wage seem to be I(1). Some problems arise with the joint hypothesis, F-tests, for absence of trend or drift and presence of unit root, probably due to the low power of the joint tests. For example, in the case where the coefficient of the unit root is larger than the coefficient, different from zero, of the drift, the F-test, $\Phi_2$, is accepted. In our case it often leads to acceptance of the hypothesis of non-stationary series without drift (in the model 2) even though the plot of the differences shows a clear drift in the variable. This is the result for employment in industry and the public sector (Table 1) both from Dickey Fuller tests and Phillips type tests. Instead, in the case of the industrial output (Table 2) and industrial real wage (Table 4) the F-tests, $\Phi_3$ and $Z(\Phi_3)$, show the series to be stationary around a deterministic trend, even though the unit root is found via t-test. This result is probably due to the presence of a strong trend in the series. In all these ambiguous cases we tried to balance the information coming from inspection of the plots, correlograms and t-tests with the F-tests results. Tables 1, 2, 3, 4, report the results from the unit root tests for the disaggregated series, while Table 5 reports the results for the aggregate variables.
**TABLE 1**
Testing the order of integration for sectoral employment: Dickey Fuller Tests and Phillips-Perron Tests

<table>
<thead>
<tr>
<th>Lags</th>
<th>$T_T$</th>
<th>$\Phi3$</th>
<th>$\Phi2$</th>
<th>$T_\mu$</th>
<th>$\Phi1$</th>
<th>F-Test p-value</th>
<th>N-Test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lea</td>
<td>0</td>
<td>-2.55</td>
<td>3.49</td>
<td>22.61</td>
<td>0.67</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td>$\Delta$Lea</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-7.02</td>
<td>24.70</td>
<td>0.77</td>
</tr>
<tr>
<td>Lei</td>
<td>1</td>
<td>-2.10</td>
<td>4.50</td>
<td>3.20</td>
<td>-2.87</td>
<td>4.43</td>
<td>0.15</td>
</tr>
<tr>
<td>$\Delta$Lei</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-3.21</td>
<td>5.19</td>
<td>0.90</td>
</tr>
<tr>
<td>Les</td>
<td>1</td>
<td>-1.09</td>
<td>0.98</td>
<td>5.68</td>
<td></td>
<td></td>
<td>0.21</td>
</tr>
<tr>
<td>$\Delta$Les</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-4.66</td>
<td>10.92</td>
<td>0.36</td>
</tr>
<tr>
<td>Lep</td>
<td>1</td>
<td>-0.12</td>
<td>1.15</td>
<td>1.97</td>
<td>-1.54</td>
<td>3.04</td>
<td>0.91</td>
</tr>
<tr>
<td>$\Delta$Lep</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-2.27</td>
<td>2.74</td>
<td>0.96</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lags</th>
<th>$Z(T_T)$</th>
<th>$Z(\Phi3)$</th>
<th>$Z(\Phi2)$</th>
<th>$Z(T_\mu)$</th>
<th>$Z(\Phi1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lea</td>
<td>1*</td>
<td>-2.52</td>
<td>3.41</td>
<td>23.80</td>
<td></td>
</tr>
<tr>
<td>$\Delta$Lea</td>
<td>1</td>
<td></td>
<td></td>
<td>-7.04</td>
<td>24.78</td>
</tr>
<tr>
<td>$\Delta$Lea</td>
<td>6*</td>
<td></td>
<td></td>
<td>-7.03</td>
<td>24.73</td>
</tr>
<tr>
<td>Lei</td>
<td>1</td>
<td>-2.05</td>
<td>10.67</td>
<td>8.68</td>
<td></td>
</tr>
<tr>
<td>Lei</td>
<td>4*</td>
<td>-2.06</td>
<td>9.2</td>
<td>11.29</td>
<td></td>
</tr>
<tr>
<td>$\Delta$Lei</td>
<td>1</td>
<td></td>
<td></td>
<td>-3.22</td>
<td>5.20</td>
</tr>
<tr>
<td>$\Delta$Lei</td>
<td>6*</td>
<td></td>
<td></td>
<td>-3.10</td>
<td>4.38</td>
</tr>
<tr>
<td>Les</td>
<td>1</td>
<td>-0.89</td>
<td>0.65</td>
<td>27.11</td>
<td></td>
</tr>
<tr>
<td>Les</td>
<td>6*</td>
<td>-1.24</td>
<td>0.94</td>
<td>17.23</td>
<td></td>
</tr>
<tr>
<td>$\Delta$Les</td>
<td>1</td>
<td></td>
<td></td>
<td>-4.64</td>
<td>10.77</td>
</tr>
<tr>
<td>$\Delta$Les</td>
<td>6*</td>
<td></td>
<td></td>
<td>-4.86</td>
<td>11.91</td>
</tr>
<tr>
<td>Lep</td>
<td>1*</td>
<td>0.94</td>
<td>3.61</td>
<td>57.33</td>
<td></td>
</tr>
<tr>
<td>$\Delta$Lep</td>
<td>1*</td>
<td></td>
<td></td>
<td>-2.26</td>
<td>2.72</td>
</tr>
</tbody>
</table>

Critical values from Dickey Fuller (1976, 1981):
$T_T$ ($H_0: \alpha = 1$ in model 3): 2.5% -3.80, 5% -3.50, 10% -3.18
$\Phi3$ ($H_0: \alpha = 1, \beta = 0$ in model 3): 2.5% 7.81, 5% 6.73, 10% 5.61
$\Phi2$ ($H_0: \alpha = 1, \beta = 0$ in model 3): 2.5% 5.94, 5% 5.13, 10% 4.31
$T_\mu$ ($H_0: \alpha = 1$ in model 2): 2.5% -3.22, 5% -2.92, 10% -2.60
$\Phi1$ ($H_0: \alpha = 1, \mu = 0$ in model 2): 2.5% 5.80, 5% 4.86, 10% 3.94
* indicates the automatic truncation lag from Shazam program

**Note:** F-test: test for up to 1th order serial correlation.
N-test: Jarque Bera test of normality of residuals.
p-value: probability of a type I error.
### TABLE 2
Testing the order of integration for sectoral output: Dickey-Fuller Tests and Phillips-Perron Tests

<table>
<thead>
<tr>
<th>Lags</th>
<th>Tr</th>
<th>Φ3</th>
<th>Φ2</th>
<th>Τμ</th>
<th>Φ1</th>
<th>F-Test p-value</th>
<th>N-test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lya</td>
<td>1</td>
<td>-1.28</td>
<td>3.81</td>
<td>6.49</td>
<td></td>
<td>0.89</td>
<td>0.67</td>
</tr>
<tr>
<td>ΔLya</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-8.83</td>
<td>39.01</td>
<td>0.83</td>
</tr>
<tr>
<td>Lyi</td>
<td>0</td>
<td>-1.57</td>
<td>9.99</td>
<td>34.83</td>
<td></td>
<td>0.79</td>
<td>0</td>
</tr>
<tr>
<td>ΔLyi</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-4.22</td>
<td>8.94</td>
<td>0.71</td>
</tr>
<tr>
<td>Lys</td>
<td>0</td>
<td>-0.066</td>
<td>4.13</td>
<td>79.88</td>
<td></td>
<td>0.27</td>
<td>0.88</td>
</tr>
<tr>
<td>ΔLys</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-4.19</td>
<td>8.81</td>
<td>0.48</td>
</tr>
<tr>
<td>Lyp</td>
<td>1</td>
<td>-0.23</td>
<td>4.4</td>
<td>7.30</td>
<td></td>
<td>1</td>
<td>0.01</td>
</tr>
<tr>
<td>ΔLyp</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-3.82</td>
<td>7.36</td>
<td>0.60</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lags</th>
<th>Z(Tr)</th>
<th>Z(Φ3)</th>
<th>Z(Φ2)</th>
<th>Z(Τμ)</th>
<th>Z(Φ1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lya</td>
<td>1*</td>
<td>1.33</td>
<td>2.46</td>
<td>4.30</td>
<td></td>
</tr>
<tr>
<td>ΔLya</td>
<td>1</td>
<td></td>
<td>-8.81</td>
<td>38.84</td>
<td></td>
</tr>
<tr>
<td>ΔLyi</td>
<td>6*</td>
<td>-8.89</td>
<td>39.49</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lyi</td>
<td>1</td>
<td>-1.57</td>
<td>9.63</td>
<td>33.41</td>
<td></td>
</tr>
<tr>
<td>ΔLyi</td>
<td>6*</td>
<td>-1.75</td>
<td>21.41</td>
<td>78.39</td>
<td></td>
</tr>
<tr>
<td>Lys</td>
<td>1*</td>
<td></td>
<td>-4.02</td>
<td>8.86</td>
<td></td>
</tr>
<tr>
<td>ΔLys</td>
<td>4*</td>
<td>0</td>
<td>9.30</td>
<td>3.77</td>
<td></td>
</tr>
</tbody>
</table>

Critical values from Dickey Fuller (1976, 1981):
Tr (H0: α = 1 in model 3): 2.5%, -3.80, 5%, -3.50, 10%, -3.18
Φ3 (H0: α = 1, β = 0 in model 3): 2.5%, 7.81, 5%, 6.73, 10%, 5.61
Φ2 (H0: α = 1, β = 0, μ = 0 in model 3): 2.5%, 5.94, 5%, 5.13, 10%, 4.31
Τμ (H0: α = 1 in model 2): 2.5%, -3.22, 5%, -2.92, 10%, -2.60
Φ1 (H0: α = 1, μ = 0 in model 2): 2.5%, 5.80, 5%, 4.86, 10%, 3.94
* indicates the automatic truncation lag from Shazam program

**Note:** F-test: test for up to 1st order serial correlation.  
N-test: Jarque Bera test of normality of residuals.  
p-value: probability of a type I error.
## TABLE 3
Testing the order of integration for sectoral output prices: Dickey-Fuller Tests and Phillips-Perron Tests

<table>
<thead>
<tr>
<th>Lags</th>
<th>Lpa</th>
<th>ΔLpa</th>
<th>ΔΔLpa</th>
<th>Lpi</th>
<th>ΔLpi</th>
<th>ΔΔLpi</th>
<th>Lps</th>
<th>ΔLps</th>
<th>ΔΔLps</th>
<th>Lpp</th>
<th>ΔLpp</th>
<th>ΔΔLpp</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tτ</td>
<td>-2.14</td>
<td>-2.20</td>
<td>-7.02</td>
<td>-2.19</td>
<td>-1.68</td>
<td>-5.49</td>
<td>-2.50</td>
<td>-1.61</td>
<td>-5.94</td>
<td>-2.21</td>
<td>-2.39</td>
<td>-7.77</td>
</tr>
<tr>
<td>Φ3</td>
<td>2.54</td>
<td>2.43</td>
<td>24.70</td>
<td>2.44</td>
<td>1.46</td>
<td>15.12</td>
<td>3.39</td>
<td>1.29</td>
<td>17.70</td>
<td>4.01</td>
<td>2.89</td>
<td>30.35</td>
</tr>
<tr>
<td>Φ2</td>
<td>2.58</td>
<td>1.54</td>
<td>0.38</td>
<td>2.79</td>
<td>1.46</td>
<td>0.88</td>
<td>2.96</td>
<td>0.80</td>
<td>0.5</td>
<td>4.49</td>
<td>0.78</td>
<td>0.29</td>
</tr>
<tr>
<td>Φ1</td>
<td>-0.13</td>
<td>0.05</td>
<td>0.045</td>
<td>-0.06</td>
<td>0.59</td>
<td>0.82</td>
<td>-0.11</td>
<td>0.82</td>
<td>0.71</td>
<td>-0.39</td>
<td>0.37</td>
<td>0.83</td>
</tr>
<tr>
<td>F-Test p-value</td>
<td>1.21</td>
<td>0.69</td>
<td>0.078</td>
<td>1.54</td>
<td>0.59</td>
<td>0.34</td>
<td>0.91</td>
<td>0.82</td>
<td>0.01</td>
<td>1.29</td>
<td>0.37</td>
<td>0.67</td>
</tr>
<tr>
<td>N-Test p-value</td>
<td>0.43</td>
<td>0.69</td>
<td>0.045</td>
<td>0.05</td>
<td>0.59</td>
<td>0.34</td>
<td>0.82</td>
<td>0.82</td>
<td>0.01</td>
<td>0.78</td>
<td>0.37</td>
<td>0.83</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lags</th>
<th>Z(Tτ)</th>
<th>Z(Φ3)</th>
<th>Z(Φ2)</th>
<th>Z(Tμ)</th>
<th>Z(Φ1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lpa</td>
<td>1</td>
<td>-1.67</td>
<td>4</td>
<td>11.69</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5*</td>
<td>-1.70</td>
<td>2.83</td>
<td>6.57</td>
<td></td>
</tr>
<tr>
<td>ΔLpa</td>
<td>*</td>
<td>-2.16</td>
<td>2.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔΔLpa</td>
<td>1</td>
<td>-7.04</td>
<td>24.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔΔLpa</td>
<td>6*</td>
<td>-7.36</td>
<td>26.87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lpi</td>
<td>1</td>
<td>-2.3</td>
<td>5.32</td>
<td>11.94</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2*</td>
<td>-2.21</td>
<td>4.96</td>
<td>10.6</td>
<td></td>
</tr>
<tr>
<td>ΔLpi</td>
<td>1</td>
<td>-1.98</td>
<td>2.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔΔLpi</td>
<td>2*</td>
<td>-1.93</td>
<td>1.92</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lps</td>
<td>1</td>
<td>-1.42</td>
<td>4.76</td>
<td>25.24</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3*</td>
<td>-1.39</td>
<td>3.32</td>
<td>15.57</td>
<td></td>
</tr>
<tr>
<td>ΔLps</td>
<td>1*</td>
<td>-1.64</td>
<td>1.36</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔΔLps</td>
<td>1</td>
<td>-5.94</td>
<td>17.69</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔΔLps</td>
<td>2*</td>
<td>-5.94</td>
<td>17.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lpp</td>
<td>1</td>
<td>-1.53</td>
<td>5.59</td>
<td>39.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2*</td>
<td>-1.54</td>
<td>4.61</td>
<td>30.38</td>
<td></td>
</tr>
<tr>
<td>ΔLpp</td>
<td>1*</td>
<td>-2.29</td>
<td>2.63</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔΔLpp</td>
<td>1</td>
<td>-7.84</td>
<td>30.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔΔLpp</td>
<td>2*</td>
<td>-7.85</td>
<td>30.93</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Critical values from Dickey Fuller (1976, 1981):
- Tτ (H0: α = 1 in model 3): 2.5% -3.80, 5% -3.50, 10% -3.18
- Φ3 (H0: α = 1, β = 0 in model 3): 2.5% 7.81, 5% 6.73, 10% 5.61
- Φ2 (H0: α = 1, β = 0 in model 3): 2.5% 5.94, 5% 5.13, 10% 4.31
- Tμ (H0: α = 1 in model 2): 2.5% -3.22, 5% -2.92, 10% -2.60
- Φ1 (H0: α = 1, μ = 0 in model 2): 2.5% 5.80, 5% 4.86, 10% 3.94

* indicates the automatic truncation lag from Shazam program

Note: F-test: test for up to 1th order serial correlation.
N-test: Jarque Bera test of normality of residuals.
p-value: probability of a type I error
TABLE 4
Testing the order of integration for sectoral real wages: Dickey-Fuller Tests and Phillips-Perron Tests

<table>
<thead>
<tr>
<th>Lags</th>
<th>$T_r$</th>
<th>$\Phi 3$</th>
<th>$\Phi 2$</th>
<th>$T_\mu$</th>
<th>$\Phi 1$</th>
<th>F-Test p-value</th>
<th>N-Test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lwra</td>
<td>0</td>
<td>-1.53</td>
<td>1.19</td>
<td>17.11</td>
<td></td>
<td>0.67</td>
<td>0.39</td>
</tr>
<tr>
<td>ΔLwra</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-5.98</td>
<td>17.88</td>
<td>0.74</td>
</tr>
<tr>
<td>Lwri</td>
<td>0</td>
<td>-1.45</td>
<td>8.42</td>
<td>59.95</td>
<td>9.43</td>
<td>0.26</td>
<td>0.61</td>
</tr>
<tr>
<td>ΔLwri</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-4.09</td>
<td>8.43</td>
<td>0.44</td>
</tr>
<tr>
<td>Lwrs</td>
<td>1</td>
<td>-0.41</td>
<td>4.63</td>
<td>5.32</td>
<td>1.82</td>
<td>0.05</td>
<td>0.59</td>
</tr>
<tr>
<td>ΔLwrs</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.11</td>
<td>0.71</td>
</tr>
<tr>
<td>Lwrep</td>
<td>0</td>
<td>-1.53</td>
<td>1.19</td>
<td>10.87</td>
<td>-4.82</td>
<td>11.62</td>
<td>0.63</td>
</tr>
<tr>
<td>ΔLwrep</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lags</th>
<th>$Z(T_r)$</th>
<th>$Z(\Phi 3)$</th>
<th>$Z(\Phi 2)$</th>
<th>$Z(T_\mu)$</th>
<th>$Z(\Phi 1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lwra</td>
<td>1*</td>
<td>-1.59</td>
<td>1.28</td>
<td>16.22</td>
<td></td>
</tr>
<tr>
<td>ΔLwra</td>
<td>1</td>
<td></td>
<td>-5.97</td>
<td>17.87</td>
<td></td>
</tr>
<tr>
<td>ΔLwra</td>
<td>3*</td>
<td></td>
<td>-5.97</td>
<td>17.87</td>
<td></td>
</tr>
<tr>
<td>Lwri</td>
<td>1*</td>
<td>-1.45</td>
<td>7.30</td>
<td>50.89</td>
<td></td>
</tr>
<tr>
<td>ΔLwri</td>
<td>1*</td>
<td></td>
<td>-4.05</td>
<td>8.24</td>
<td></td>
</tr>
<tr>
<td>Lwrs</td>
<td>1</td>
<td>-0.031</td>
<td>7.02</td>
<td>15.68</td>
<td></td>
</tr>
<tr>
<td>ΔLwrs</td>
<td>3*</td>
<td>-0.25</td>
<td>4.90</td>
<td>10.89</td>
<td></td>
</tr>
<tr>
<td>Lwrep</td>
<td>1*</td>
<td>-1.71</td>
<td>1.50</td>
<td>9.17</td>
<td></td>
</tr>
<tr>
<td>ΔLwrep</td>
<td>1*</td>
<td></td>
<td>-4.83</td>
<td>11.68</td>
<td></td>
</tr>
</tbody>
</table>

Critical values from Dickey Fuller (1976, 1981):
- $T_r$ (H₀: α = 1 in model 3): 2.5% -3.80, 5% -3.50, 10% -3.18
- $\Phi 3$ (H₀: α = 1, β = 0 in model 3): 2.5% 7.81, 5% 6.73, 10% 5.61
- $\Phi 2$ (H₀: α = 1, β = 0, μ = 0 in model 3): 2.5% 5.94, 5% 5.13, 10% 4.31
- $T_\mu$ (H₀: α = 1 in model 2): 2.5% -3.22, 5% -2.92, 10% -2.60
- $\Phi 1$ (H₀: α = 1, μ = 0 in model 2): 2.5% 5.80, 5% 4.86, 10% 3.94

* indicates the automatic truncation lag from Shazam program

Note: F-test: test for up to 1st order serial correlation.
N-test: Jarque Bera test of normality of residuals.
p-value: probability of a type I error
### TABLE 5
Testing the order of integration for aggregated series: Dickey-Fuller Tests and Phillips-Perron Tests

<table>
<thead>
<tr>
<th>Variable</th>
<th>Lags</th>
<th>$T\tau$</th>
<th>$\Phi_3$</th>
<th>$\Phi_2$</th>
<th>$T\mu$</th>
<th>$\Phi_1$</th>
<th>F-Test p-value</th>
<th>N-Test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Let</td>
<td>1</td>
<td>-2.23</td>
<td>2.52</td>
<td>5.10</td>
<td>-2.03</td>
<td>3.11</td>
<td>0.62</td>
<td>0.13</td>
</tr>
<tr>
<td>$\Delta$Let</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td>-4.91</td>
<td>12.11</td>
<td>0.41</td>
<td>0.80</td>
</tr>
<tr>
<td>Lyt</td>
<td>0</td>
<td>-0.49</td>
<td>6.92</td>
<td>63.97</td>
<td>-4.29</td>
<td>9.26</td>
<td>0.72</td>
<td>0</td>
</tr>
<tr>
<td>$\Delta$Lyt</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.72</td>
<td>0</td>
</tr>
<tr>
<td>Lw</td>
<td>1</td>
<td>-0.78</td>
<td>3.83</td>
<td>5.90</td>
<td>-3.24</td>
<td>5.21</td>
<td>0.18</td>
<td>0.10</td>
</tr>
<tr>
<td>$\Delta$Lw</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.50</td>
<td>0.65</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Lags</th>
<th>$Z(T\tau)$</th>
<th>$Z(\Phi_3)$</th>
<th>$Z(\Phi_2)$</th>
<th>$Z(T\mu)$</th>
<th>$Z(\Phi_1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Let</td>
<td>1*</td>
<td>-2.33</td>
<td>3.03</td>
<td>10.57</td>
<td>-4.89</td>
<td>12.00</td>
</tr>
<tr>
<td>$\Delta$Let</td>
<td>1*</td>
<td></td>
<td></td>
<td></td>
<td>-4.89</td>
<td>12.00</td>
</tr>
<tr>
<td>Lyt</td>
<td>1*</td>
<td>-0.52</td>
<td>6.57</td>
<td>60.42</td>
<td>-4.28</td>
<td>9.19</td>
</tr>
<tr>
<td>$\Delta$Lyt</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>-4.39</td>
<td>9.72</td>
</tr>
<tr>
<td>Lw</td>
<td>2*</td>
<td>-0.51</td>
<td>6.85</td>
<td>49.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$Lw</td>
<td>1*</td>
<td></td>
<td></td>
<td></td>
<td>-3.24</td>
<td>5.21</td>
</tr>
</tbody>
</table>

Critical values from Dickey Fuller (1976, 1981):
$T\tau$ ($H_0$: $\alpha = 1$ in model 3): 2.5% -3.80, 5% -3.50, 10% -3.18
$\Phi_3$ ($H_0$: $\alpha = 1$, $\beta = 0$ in model 3): 2.5% 7.81, 5% 6.73, 10% 5.61
$\Phi_2$ ($H_0$: $\alpha = 1$, $\beta = 0$, $\mu = 0$ in model 3): 2.5% 5.94, 5% 5.13, 10% 4.31
$T\mu$ ($H_0$: $\alpha = 1$ in model 2): 2.5% -3.22, 5% -2.92, 10% -2.60
$\Phi_1$ ($H_0$: $\alpha = 1$, $\mu = 0$ in model 2): 2.5% 5.80, 5% 4.86, 10% 3.94
* indicates the automatic truncation lag from Shazam program

Note: F-test: test for up to 1th order serial correlation.
N-test: Jarque Bera test of normality of residuals.
p-value: probability of a type I error
4. Analysing the long run relationships

In this section the long run relationship between employment, output and real wage in each sectors is analysed. The concept of cointegration provides a framework for testing and estimating long run equilibrium among these non-stationary variables. Such variables are called cointegrated if they are individually I(1), but there exists a linear combination of them that is stationary, I(0). So these variables do not tend to wander but move together in the long run.

The estimation procedure proposed by Johansen (1988, 1991a) and Johansen and Juselius (1990)\(^4\) consists of a maximum likelihood estimation of a VAR, reparametrized in an ECM-form, which contains \(n\) variables, all of which I(1):

\[
4) \Delta y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta y_{t-i} + \Pi \Delta y_{t-k} + u_t,
\]

where \(\Gamma_i\) and \(\Pi\) are matrices of unknown parameters, \(\Delta y_t\) and \(\Delta y_{t-1}\) are vectors of I(0) variables, while the \(\Delta y_{t-k}\) is a vector of I(1) variables. \(\mu\) is a drift parameter, capturing the role of technical progress and \(u_t\) is a vector of disturbances. The system is balanced, in terms of degree of integration, only if \(\Pi=0\), in this case the variables are not cointegrated, or if the long run parameters of \(\Pi\) are such that \(\Pi \Delta y_{t-k}\) is also I(0). The latter case implies that the variables are cointegrated of order \(n-r\), where \(r\) is the number of cointegration vectors. If the variables are cointegrated the \(\Pi\)-matrix can be decomposed in the following way:

\[
\Pi = \alpha \beta',
\]

where \(\beta\) is the matrix of the cointegration vectors and \(\alpha\) is the weight of the cointegration vectors in each equation of the VAR. So a low \(\alpha\) indicates slow adjustment towards the estimated equilibrium state and a high coefficient indicates rapid adjustment.

Before applying the Johansen procedure, it is necessary to determine the lag length of the VAR that ensures residuals approximately white noise normal. Estimating the equation (4) the data suggest that a VAR with two lags is sufficient to whiten the residuals vector in the

\(^4\)The maximum likelihood estimation has been treated in Johansen (1988) for the model without a constant and by Johansen (1991a) and Johansen and Juselius (1990) for the model with a constant in the VAR.
agricultural sector, the industrial sector and the public administration (Table 8). For services some problems of autocorrelation arise in two equations of the VAR. Table 8 also shows two cases of non-normality of residuals in industry and services. An higher order of lags did not rectify the non-normality and autocorrelation problem.

<table>
<thead>
<tr>
<th>Equations</th>
<th>F-Test p-value</th>
<th>N-Test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM1: lca</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>ECM2: lya</td>
<td>0.54</td>
<td>0.71</td>
</tr>
<tr>
<td>ECM3: lwra</td>
<td>0.73</td>
<td>0.91</td>
</tr>
<tr>
<td>ECM1: lei</td>
<td>0.24</td>
<td>0.59</td>
</tr>
<tr>
<td>ECM2: lyi</td>
<td>0.64</td>
<td>0.006</td>
</tr>
<tr>
<td>ECM3: lwri</td>
<td>0.13</td>
<td>0.31</td>
</tr>
<tr>
<td>ECM1: les</td>
<td>0.11</td>
<td>0</td>
</tr>
<tr>
<td>ECM2: lys</td>
<td>0.05</td>
<td>0.096</td>
</tr>
<tr>
<td>ECM3: lwrs</td>
<td>0.005</td>
<td>0.40</td>
</tr>
<tr>
<td>ECM1: lrp</td>
<td>0.25</td>
<td>0.51</td>
</tr>
<tr>
<td>ECM2: lyp</td>
<td>0.054</td>
<td>0.51</td>
</tr>
<tr>
<td>ECM3: lwrp</td>
<td>0.38</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Note: F: F-test for up to 1th order serial correlation
N: Jarque-Bera test of normality
p-value: probability of a type I error

The likelihood ratio test statistics for the determination of the cointegration rank of each Π of the VARs in each sector are given in Table 9. It also reports the eigenvalues (denoted λ) and the LR-tests both for the λ_max statistics, calculated as \(-T \ln(1 - \lambda_r)\) for the eigenvalue of the rth cointegration vector, and for the Trace statistics, calculated as \(-T \sum_{i=r+1}^{p} \ln(1 - \lambda_i)\). The 95% and 90% quantiles for testing the order of r from the Osterwald-Lenum (1992) tables are reported.

If we consider λ_max test statistics, the hypothesis of one cointegration vector is accepted in agriculture at 95%, while in public administration the same hypothesis is accepted at 90%. The Trace statistics (trace test is better when the eigenvalues are similar) leads to accept one cointegration vector in industry at 90% and public administration at 95%, while in the services we accept one cointegration vector at the boundary of 90%. In general the tests do not give a clearcut result because of their low power, when the cointegration relation is close to the non-
stationary boundary. In other words, the result may be contradictory when the speed of adjustment to the hypothetical long run equilibrium is slow. Hence, in agriculture and public administration the cointegration is stronger than in industry and services because both the tests enable us to accept at least one cointegration vector.

**TABLE 9**
Testing the rank of Π matrix: agriculture, industry, services, public administration.

<table>
<thead>
<tr>
<th></th>
<th>Agriculture</th>
<th>Industry</th>
<th>Services</th>
<th>Public Administration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(λ₁ = 0.47119, λ₂ = 0.28242, λ₃ = 0.18176)</td>
<td>(λ₁ = 0.33989, λ₂ = 0.25510, λ₃ = 0.042876)</td>
<td>(λ₁ = 0.37025, λ₂ = 0.19753, λ₃ = 0.017297)</td>
<td>(λ₁ = 0.40893, λ₂ = 0.25081, λ₃ = 0.042710)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H₀</td>
<td>H₁</td>
<td>λₘₐₓ</td>
<td>95%</td>
<td>90%</td>
</tr>
<tr>
<td>r = 0</td>
<td>r = 1, r ≥ 1</td>
<td>24.2109</td>
<td>20.9670</td>
<td>18.5980</td>
</tr>
<tr>
<td>r ≤ 1</td>
<td>r = 2, r ≥ 2</td>
<td>12.6113</td>
<td>14.0690</td>
<td>12.0710</td>
</tr>
<tr>
<td>r ≤ 2</td>
<td>r = 3, r ≥ 3</td>
<td>7.6230</td>
<td>3.7620</td>
<td>2.6870</td>
</tr>
</tbody>
</table>

Critical values: Osterwald-Lenum 1992
H₁: r ≥ 0, 1... is the alternative hypothesis for the λₘₐₓ test
H₁: r ≥ 0, 1... is the alternative hypothesis for the Trace test.

Table 10 reports the stationary cointegration relations, that can be derived from the Trace tests, and the corresponding weights (α vectors). All the cointegration vectors reflect the positive relationship between employment and output and a negative link between employment and real
wage. The positive coefficient of the real wage in the public sector seems not significantly different from zero. We will test this hypothesis later.

The sign on output in the agricultural cointegration vector is positive even if agricultural employment has a negative trend while the output has a positive trend. However, from the plot of the series it is evident that the output in agriculture increases less than output in the other sectors (Fig. 6), whereas the rapid growth of the agricultural real wage markedly reduces the gap with the other wages (Fig. 3). Hence the negative trend in agricultural employment is partially captured, in the cointegration vector, by the increase of the wage with respect to output. Moreover, the principal factor accounting for the negative trend in employment is the growth of productivity that is well captured by the constant in the VAR. This is another fact explaining the estimated positive elasticity between employment and output in the long run relationship.

The estimated cointegration vectors presented above are obtained from the estimation of equation (4) under the assumption that the deterministic trend contained in the series, captured by the constant of the VAR, cancel out in the cointegration relationship. If this is not the case a deterministic trend should have been included in the cointegration vector (Campbell and Perron 1991, Johansen and Juselius 1990, Johansen 1991c, 1991d, Juselius 1991, Ogaki and Park 1990). In our case it is performed because the cointegration residuals in Fig.1 are trended. This should mean that the series are cointegrated up to a deterministic trend (stochastic cointegration): in other words, there is some linear growth, which our model cannot totally explain. We also recall that in these two sectors the evidence of cointegration is not strong, so it could be another reason for trended residuals. The inclusion of a time trend in the cointegration vectors does not lead to a significantly different from zero coefficient of the time trend. Hence the estimations are less efficient and the tests have less power than those presented in the previous section for the case of "classical cointegration".
FIG. 1

Residuals of cointegrating vector: AGRICULTURE

Residuals of cointegrating vector: INDUSTRY
Residuals of cointegrating vector: SERVICES

Residuals of cointegrating vector: PUBLIC ADMINISTRATION
TABLE 10
Estimated cointegration vector and corresponding weight

<table>
<thead>
<tr>
<th>Variables</th>
<th>$\beta_1^1(A)$</th>
<th>$\beta_1^1(I)$</th>
<th>$\beta_1^1(S)$</th>
<th>$\beta_1^1(P)$</th>
<th>$\alpha_1(A)$</th>
<th>$\alpha_1(I)$</th>
<th>$\alpha_1(S)$</th>
<th>$\alpha_1(P)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>LE</td>
<td>-1.00</td>
<td>-1.00</td>
<td>-1.00</td>
<td>-1.00</td>
<td>-0.23</td>
<td>0.070</td>
<td>0.075</td>
<td>0.077</td>
</tr>
<tr>
<td>LY</td>
<td>0.53</td>
<td>1.36</td>
<td>0.81</td>
<td>1.11</td>
<td>-0.12</td>
<td>0.25</td>
<td>0.08</td>
<td>-0.22</td>
</tr>
<tr>
<td>LW</td>
<td>-0.60</td>
<td>-1.39</td>
<td>-0.77</td>
<td>0.03</td>
<td>0.58</td>
<td>0.32</td>
<td>0.27</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

Note: $\beta(A)$ : represents the cointegration vector in agriculture
$\beta(I)$ : represents the cointegration vector in industry
$\beta(S)$ : represents the cointegration vector in services
$\beta(P)$ : represents the cointegration vector in public administration
$\alpha(.)$ : represents the corresponding weight

4.1 Weak exogeneity, long run exclusion and some structural hypotheses

Having assumed one long run relationship in each sector, we may test restrictions on the cointegration vector and on the relative adjustment vector ($\alpha$) by the likelihood ratio test in order to test the null hypothesis that the restriction is valid. The likelihood ratio test is

$$LR(\alpha, \beta') = -T \sum_{t=1}^{T} \ln[(1 - \lambda^R) / (1 - \lambda^{UN})]$$

where $r$ is the order of cointegration vector established through the Trace tests and/or the $\lambda_{\text{max}}$ tests, $\lambda^R$ represents the estimated characteristic roots from the restricted model and $\lambda^{UN}$ represents the roots from the unrestricted model. Under the null that the restriction is valid, the test is asymptotically distributed as a $\chi^2$ ($rs$), where $s$ is the number of restrictions imposed on the cointegration vectors.

The concept of weak exogeneity can be utilised to motivate the reduction of the dimension of the VAR. The condition for the variables to be weakly exogenous for $\beta$ is that the associated coefficient of adjustment, $\alpha$, be equal to zero, implying that the long run parameters $\beta$ can be estimated efficiently without the equation for the weakly exogenous variables. In our case the coefficients of the $\alpha$ vectors are small in the cases of the labour equation in the industrial
sector, in services and the public sector and in the output equation in the services. This means that the labour demand equation does not adjust to the long run target.

By testing $\alpha_{1,1}(I) = 0$, we check that the employment in industry is weakly exogenous. This means that the labour demand in industry fails, i.e. employment enters as an independent variable in the other equation of VAR. This is also true for services and public administration testing $\alpha_{1,1}(S) = 0$ and $\alpha_{1,1}(P) = 0$.

The test that $\alpha_{1,1}(I) = 0$ yields a likelihood ratio test $LR = 0.98$, which compared with the 5% critical value, $\chi^2(1) = 3.84$, enables an acceptance of the null hypothesis that Lei is weakly exogenous with respect to the rest of the system. The corresponding t-statistic, calculated by taking the square root of the $\chi^2(1)$ likelihood ratio statistic, is $t = 0.99$.

The test that $\alpha_{1,1}(S) = 0$ yields a $LR = 1.20$ and a t-statistic = 1.09, while the test that $\alpha_{1,1}(P) = 0$ yields a $LR = 1.81$ and a t-statistic = 1.34. Both tests compared, with the 5% critical value above, enable us to accept the restrictions, so also Lex and Lexp are weakly exogenous to the rest of the system of equations (VAR for services sector and VAR for the public administration).

For services we can also test if output is weakly exogenous, for $\alpha_{1,2}(S)$ is small 0.08. The test $\alpha_{1,2}(S) = 0$ yields a $LR = 0.789$ and a t-statistic = 0.888 that enables us to accept the null. The joint restriction $\alpha_{1,1}(S) = 0$ and $\alpha_{1,2}(S) = 0$ yields a $LR = 2.59$, which compared with the 5% critical value, $\chi^2(2) = 5.99$, enables us to accept the restriction. So in the services there are two weakly exogenous variables Lex and Lexp.

The employment equation in agriculture is not weakly exogenous, in fact it is easy to reject the null $\alpha_{1,1}(A) = 0$, the test is $LR = 5.02$ and the t-statistic = 2.24.

Tests of the significance of the other adjustment coefficients were also performed, even if the coefficients did not seem too small. In agriculture $\alpha_{1,2}(A) = 0$ ($LR = 0.544$, t-statistic = 0.73) is accepted, while $\alpha_{1,3}(A) = 0$ ($LR = 8.48$, t-statistic = 2.91) is rejected. In industry $\alpha_{1,2}(I) = 0$ ($LR = 1.27$, t-statistic = 1.12) is accepted, while $\alpha_{1,3}(I) = 0$ ($LR = 4.56$, t-statistic = 2.13) is rejected. In services $\alpha_{1,2}(S) = 0$ ($LR = 0.78$, t-statistic = 0.88) is accepted, while $\alpha_{1,3}(S) = 0$ ($LR = 3.67$, t-statistic = 1.97) is also accepted, compared with the 5% critical value $\chi^2(1) = 3.84,$
but accepted, when compared with the 10% critical value $\chi^2(1) = 2.71$. In the public sector $\alpha_{1,2}(P) = 0$ (LR = 0.31, t-statistic = 0.55) is accepted, while $\alpha_{1,3}(P) = 0$ (LR = 3.67, t-statistic = 1.97) is rejected with the 10% critical value.

So there is an ECM in agriculture for employment and real wage conditioning on output, an ECM in industry for real wage conditioning on employment, and output, an ECM in the private sector for real wage conditioning to employment and output, and finally an ECM in the public sector for output conditioning to employment and real wage. This means that the labour demand in industry, services and public administration does not adjust to the long run equilibrium and it is possible to specify only an equation in the difference to take into account the short-run movements of the employment.

The difficulty in identifying the labour demand could be due to the interaction between demand and supply shocks. If the supply shocks prevail with respect to the demand shocks it is easier to identify a labour demand and a negative relation between employment and real wage, while if the demand shocks prevail it is possible to identify a wage equation, i.e. a positive relation between real wage and employment. This could be our case because an endogenous real wage is found. However, the real wage relation in industry and services captures a negative long run relation between wages and employment and a positive long run relation between output and employment, so it is difficult to interpret these relations in terms of a wage equation because of the incorrect sign of employment. In public administration instead we find a simple output equation capturing the positive relation between output and employment.

Different linear restrictions on each cointegration vector are also performed, in order to verify the significance of the coefficients. Actually it is possible that some variables are not relevant for the long run relations but are important for the short run behaviour of the dependent variables. In this case they are excluded from the cointegration vector. The likelihood ratio tests and the derived t-statistics\textsuperscript{5} enable us to say that the coefficients on real wages, except in public administration, and on output are significant in each sector, compared with the 10% critical value in industry and private services. The hypothesis that the real wage in the public sector is zero,

\textsuperscript{5}The t-statistics can be derived only in the case of one cointegration vector.
H_{0\beta}(1, b, 0) with an estimated b = 1.16 (Table 12), yields an LR = 0.41 which compared with the 10% critical value, \(\chi^2(1) = 2.71\), enables us to accept the restriction. The coefficient on employment is significant in each sector, compared with the 10% critical value in agriculture, industry and services.

Table 11 reports the normalisation of the cointegration vectors with respect to "endogenous" variables found with the \(\alpha\)-restrictions. It also reports the t-statistics for the significance of the coefficients. The long run equations can be written as follows

**TABLE 11**
Normalised cointegration vectors based on the \(\alpha\)-restriction

<table>
<thead>
<tr>
<th></th>
<th>Employment</th>
<th>Output</th>
<th>Real wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture 1</td>
<td>-1</td>
<td>0.53</td>
<td>-0.60</td>
</tr>
<tr>
<td></td>
<td>(1.82)</td>
<td>(2.46)</td>
<td>(2.44)</td>
</tr>
<tr>
<td>Agriculture 2</td>
<td>-1.66</td>
<td>0.88</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>(1.82)</td>
<td>(2.46)</td>
<td>(2.44)</td>
</tr>
<tr>
<td>Industry</td>
<td>-0.71</td>
<td>0.97</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>(1.85)</td>
<td>(1.66)</td>
<td>(1.70)</td>
</tr>
<tr>
<td>Services</td>
<td>-1.29</td>
<td>1.05</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>(1.86)</td>
<td>(1.72)</td>
<td>(1.85)</td>
</tr>
<tr>
<td>Publ. Administ.</td>
<td>0.89</td>
<td>-1</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>(2.52)</td>
<td>(2.57)</td>
<td>(0.64)</td>
</tr>
</tbody>
</table>

Note: t-statistics in brackets derived from the LR tests on the cointegration vector coefficient
Agriculture 1 and Agriculture 2 are two different normalisation, with respect to real wage and employment, of the same cointegration vector.

Another reason for performing restrictions is connected with the possibility of finding relations that have equal coefficients with opposite signs corresponding to a long run unit
elasticity (structural hypotheses). Let us take the hypotheses of homogeneity restrictions on the cointegration vectors as $H(E, Y, W)$, where $E$ is the coefficient of employment, $Y$ on output and $W$ on the real wage.

In agriculture the hypothesis $H_1\beta_a(-1, a, -a)$ yields a LR = 0.047, that compared with the 5% critical value, $\chi^2(1) = 3.84$, enables us to accept the restriction and yields an estimated $a = 0.63$. This implies a long run equilibrium in which the employment is determined equally by real wage and output. Normalising for the agricultural real wage, the same hypothesis becomes $H_2\beta_a(b, 1, -1)$, with an estimated coefficient of employment $b = -1.58$. The hypothesis $H_3\beta_a(-1, 1, -1)$ on both the normalisations is rejected.

In industry the hypothesis $H_1\beta(-1, 1, -1)$ yields an LR = 2.36, which, compared with the 5% critical value, $\chi^2(2) = 5.99$, enables us to accept the restriction. This interesting result implies that in the long run the real wage is equal to the average product of labour plus a constant, or in other words, the change in the real wage is equal to the change in productivity. This means that there is no evidence of a redistribution of income in favour of labour input, because the long run product wages and productivity move together. So in this long-run relationship it seems difficult to find the reasons behind the increase in industrial unemployment during the 1980s\(^6\).

In services the same hypothesis is rejected, yielding LR = 8.16. Instead the hypothesis of unity elasticity between real wage and output, $H_1\beta_a(c, 1, -1)$, yields an LR = 0.31 which, compared with the 5% critical value, $\chi^2(1)$, enables the restriction to be accepted. The estimated coefficient for employment is $c = -1.24$.

These results offer no evidence for attributing a predominant role to real wage or output in the long run in explaining the movements in employment or, at least, not in agriculture and industry. The new cointegration vectors based on the latter restrictions are reported in Table 12.

\(^6\)The same conclusion is in Zenezini (1989).
TABLE 12
Cointegration vectors based on the β-restrictions

<table>
<thead>
<tr>
<th></th>
<th>Employment</th>
<th>Output</th>
<th>Real wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1</td>
<td>0.63</td>
<td>-0.63</td>
</tr>
<tr>
<td>Agriculture 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture 2</td>
<td>-1.58</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Industry</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Services</td>
<td>-1.24</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Publ. Administ.</td>
<td>1.16</td>
<td>-1</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Agriculture 1 and Agriculture 2 are two different normalisation of the same cointegration vector.

4.2 Aggregate long run relationship

A result of cointegration is obtained from the aggregate estimation. Table 13 reports diagnostic tests for serial correlation and normality from equation 4 for aggregate series. This shows that one lag is sufficient to make the residual vector of the VAR serially uncorrelated and only the output equation fails the test of normality due to fat tails in the distribution. The different lag length of the VAR confirms the important result in Lippi (1988) that the aggregation modifies the dynamics. In our case the aggregation leads to a simplification of the dynamics as in Altonji and Ashenfelter (1980) but it could also induce a more dynamically complex macro equation. Thus a different dynamic structure from micro to macro is a first indicator of the weakness of the theoretical position of those who consider the aggregate Error Correction Model as being based on the maximising representative agent.
TABLE 13
Diagnostic tests for the aggregate VAR(1)

<table>
<thead>
<tr>
<th>Equations</th>
<th>F-Test p-value</th>
<th>N-Test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM1: let</td>
<td>0.76</td>
<td>0.55</td>
</tr>
<tr>
<td>ECM2: lty</td>
<td>0.063</td>
<td>0.20</td>
</tr>
<tr>
<td>ECM3: lw</td>
<td>0.48</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: F: F-test for up to 1th order serial correlation
N: Jarque-Bera test of normality
p-value: probability of a type I error

From the likelihood ratio tests (See Table14) there is clearly one cointegration vector but there may be two from the \( \lambda_{\text{max}} \) test. The acceptance of one or more cointegration relationships from both the tests immediately leads to more stationary residuals than in the disaggregate case (Fig.2). The coefficient of the second cointegration vector does not seem to offer a different economic interpretation with respect to the first vector. For this reason we consider only the first estimated long run relationship normalised with respect to employment: (-1, 0.95, -0.78). The signs are correct and reflect the expected negative relation between employment and real wage and the positive relation with the output. The \( \alpha \)-vector contains adjustment coefficients that are significantly different from zero: (0.20, 0.25, 0.58). So in this case it is possible to specify an ECM equation for employment to take into account the short-run dynamic and the adjustment to the target of steady state.

The hypothesis of equality between real wage and average product of labour is rejected since \( H(-1, 1 -1) \) leads to an LR = 11.87 which, compared with the 5% critical value, \( \chi^2(1) \), enables us to reject the restriction. On the contrary, \( H(-1, 1, -0.82) \) leads to an LR = 0.052 which enables acceptance of unity elasticity between employment and output. This restriction describes a long run relation between average product of labour and wage in which the redistribution of income is in favour of workers, even if from the disaggregated analysis this restriction could not be accepted.
TABLE 14
Testing the rank of \( \Pi \) matrix: aggregate variables

\( (\lambda_1 = 0.60501, \lambda_2 = 0.32898, \lambda_3 = 0.03204) \)

<table>
<thead>
<tr>
<th>( H_0 )</th>
<th>( H_1 )</th>
<th>( \lambda_{\text{max}} )</th>
<th>95%</th>
<th>90%</th>
<th>Trace</th>
<th>95%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r = 0 )</td>
<td>( r = 1, r \geq 1 )</td>
<td>36.226</td>
<td>21.074</td>
<td>18.904</td>
<td>53.056</td>
<td>31.525</td>
<td>28.709</td>
</tr>
<tr>
<td>( r \leq 1 )</td>
<td>( r = 2, r \geq 2 )</td>
<td>15.559</td>
<td>14.900</td>
<td>12.912</td>
<td>16.829</td>
<td>17.953</td>
<td>15.663</td>
</tr>
<tr>
<td>( r \leq 2 )</td>
<td>( r = 3, r \geq 3 )</td>
<td>1.270</td>
<td>8.176</td>
<td>6.503</td>
<td>1.270</td>
<td>8.176</td>
<td>6.503</td>
</tr>
</tbody>
</table>

Critical values: Osterwald-Lenum 1992

\( H_1: r = 0, 1... \) is the alternative hypothesis for the \( \lambda_{\text{max}} \) test

\( H_1: r \geq 0, 1... \) is the alternative hypothesis for the Trace test.

Fig.2

Residuals of aggregated cointegrating vector
The differences between the aggregate and disaggregate result can be summarised as follows.

1) The sectoral cointegration is not strong owing to the non-uniformity of the result of the $\lambda_{max}$ and Trace tests. This weakness is moreover reinforced by a simple inspection of the cointegration residuals in Fig.1. They do not seem $I(0)$. Instead the aggregate result shows a stronger and clearer cointegration relation both from the tests and from an inspection of the cointegration residuals (Fig.2).

2) The disaggregate variables do not cointegrate to a labour demand in three sectors: industry, services and public sector, for the respective coefficients of adjustment to the long run equilibria are not significantly different from zero. This means that the labour demand equation does not have an ECM form. In services and industry it is also difficult to identify a long run relation that makes economic sense and in the public sector we identify only a simple output equation. On the contrary at the aggregate level it is possible to identify a clear labour demand equation with an ECM form.

3) The accepted restriction on the cointegration vector is different in each sector and does not reflect the restriction at aggregate level.

4) The dynamics is substantially modified in the aggregation process.

All the results suggest that the information coming from the aggregate cointegration relationship and the corresponding ECM representation should be treated with caution.

5. Micro and macro cointegration

Necessary and sufficient conditions for micro-cointegration to imply macro-cointegration and vice versa are well defined in Gonzalo (1992). They are very restrictive and even more restrictive if log-linear models are involved. In Lippi 1986 these conditions are defined such that disaggregate log-linear cointegration goes through the aggregation process. In the log-linear case
the relevant conditions from an economic point of view are the following: the logs of the micro variables must cointegrate in each sector with the common cointegration vector \((1, -a)\) and the logs of the micro regressors must cointegrate across the sectors with cointegration vector \((1, -1)\). If they are true the aggregate cointegration vector is \((1, -a)\).

If at least one of these conditions is not satisfied the macro cointegration becomes only a chance event. The result at point 3) above suggests that the first condition is not satisfied in our case. Hence, it seems highly implausible that macro cointegration stems from micro cointegration. Rather macro cointegration probably emerges *empirically* as an aggregation effect from non-cointegrated or badly cointegrated micro variables (see point 1 above). One reason for this could be the occurrence in the micro series of idiosyncratic, \(I(1)\), components which prevent cointegration at the disaggregate level, but nearly cancel out when aggregation is performed. This point can be described by the following example.

Let \(y_{it}\) and \(x_{it}\) be two variables of sector \(i\) (say output and employment). Each series is composed of a common \(I(1)\) component, denoted by \(\tau_t\) and by an \(I(1)\) idiosyncratic component, denoted by \(\phi_{it}\) and \(\psi_{it}\), i.e,

\[
y_{it} = \tau_t + \phi_{it}
\]

\[
x_{it} = \tau_t + \psi_{it}
\]

where \(\phi_{it}\) is orthogonal to \(\tau_t\) and \(\phi_{it}, i \neq j\), while \(\psi_{it}\) is orthogonal to \(\tau_t\) and \(\psi_{it}, i \neq j\), (at all leads and lags). The aggregated series are

\[
y_t = \sum_{i=1}^{n} y_{it} = n\tau_t + \phi_t
\]

\[
x_t = \sum_{i=1}^{n} x_{it} = n\tau_t + \psi_t
\]

where \(\phi_t = \sum_{i=1}^{n} \phi_{it}\) and \(\psi_t = \sum_{i=1}^{n} \psi_{it}\). Furthermore, let us assume for simplicity equal variances for the changes in the idiosyncratic components of different sectors, i.e \(\text{Var}(\Delta \phi_{it}) = \sigma_{\phi}^2\) and \(\text{Var}(\Delta \psi_{it}) = \sigma_{\psi}^2\), \(\forall i\). At the aggregate level we obtain
\begin{align*}
\text{Var}(\Delta n_t) &= n^2 \sigma_i^2 \\
\text{Var}(\Delta \phi_t) &= n \sigma_\phi^2 \\
\text{Var}(\Delta \psi_t) &= n \sigma_\psi^2.
\end{align*}

Hence the variance of the change in the common component grows with \( n^2 \), whereas that of the change in the idiosyncratic components grows only with \( n \). The reduction in the relative weights of the idiosyncratic components at the aggregate level can lead to the acceptance of cointegration of the macro variables even if \( n \) is small. If for instance \( \sigma_i^2 = \sigma_\phi^2 = \sigma_\psi^2 = 1 \) and \( n = 4 \), aggregate variances are \( \text{Var}(\Delta n_t) = 16 \), \( \text{Var}(\Delta \phi_t) = 4 \), and \( \text{Var}(\Delta \psi_t) = 4 \). While at the micro level the fraction of the total variance explained by the common trend is only 1/2, at the macro level it is 16/20.

6. Conclusion

From application of multivariate cointegration analysis technique we find that employment, real wage and output cointegrate to a labour demand at the aggregate level. This macro relationship does not seem to reflect micro behaviours owing to the different dynamics and the difficulty in identifying a labour demand, at least in three sectors of the economy: industry, services and public administration. Moreover the macro variables cointegrate better than the micro. This fact is evident from inspection of the cointegration residuals that at the aggregate level are more stationary. This result could be due to the presence of \( I(1) \) idiosyncratic components in the micro series that cancel out at the aggregate level, leading to acceptance of the cointegration test.

The conclusion is that the macro cointegration emerges as a spurious result of the aggregation process and the estimation of an aggregate Error Correction Model does not seem to have an empirical micro background.
Appendix

Fig. 3  Real Wage: Agriculture, Industry and Services

Fig. 4  Real Wage: Industry, Services and Public Administration
Fig. 7  Output: Industry, Services and Public Administration

Fig. 8  Output: Aggregated Output, Industry and Services
Fig. 9  Employment: Agriculture, Industry and Services

Fig. 10  Employment: Industry, Services and Public Administration
Fig. 11 Employment: Aggregated Employment, Industry and Services
References


J.Y. Campell - P. Perron (1991), 'Pitfalls and Opportunities: What Macroeconomists should Know about Unit Roots', mimeo.


____ (1991c), 'The Role of the Constant Term in Cointegration Analysis of non Stationary Time series', Institute of Mathematical Statistics, University of Copenhagen.


K. Juselius (1991), 'Long Run Relation in Australian Monetary Data', *Discussion Paper* 91-18, Institute of Economics, University of Copenhagen


40
Materiali di discussione

24. Fernando Vianello [1987] “Effective Demand and the Rate of Profits: Some Thoughts on Marx,
40. Leonardo Paggi [1988] “Americanismo e riformismo. La socialdemocrazia europea nell’economia mondiale aperta” pp. 120.


52. Paolo Silvestri [1989] “Il bilancio dello stato” pp. 34


55. Paolo Silvestri [1990] “Sull’autonomia finanziaria delle Università” pp. 11


64. Mario Forni [1990] “Incertezza, informazione e mercati assicurativi: una rassegna” pp. 37


70. Margherita Russo [1990] “Cambiamento tecnico e distretto industriale: una verifica empirica” pp. 115


74. Enrico Giovannetti [1990] “Illusioni ottiche negli andamenti delle grandezze distributive: la scala
mobile e l’"appiattimento" delle retribuzioni in una ricerca" pp. 120


77. Antonietta Bassetti e Costanza Torricelli [1990] "Il portafoglio ottimo come soluzione di un gioco bargaining" pp. 15

78. Antonietta Bassetti e Costanza Torricelli [1990] "Una riqualificazione dell’approccio bargaining alla selezioni di portafoglio" pp. 4

79. Mario Forni [1990] "Una nota sull’errore di aggregazione" pp. 6

80. Francesca Bergamini [1991] "Alcune considerazioni sulle soluzioni di un gioco bargaining" pp. 21


84. Sebastiano Brusco e Sergio Paba [1991] "Connessioni, competenze e capacità concorrenziale nell'industria della Sardegna" pp. 25

85. Claudio Girmaldi, Rony Hamoui, Nicola Rossi [1991] "Non marketable assets and households' portfolio choices: a case study of Italy" pp. 38


89. Maria Cristina Marcuzzo [1992] "La relazione salari-occupazione tra rigidità reali e rigidità nominali" pp. 30

90. Mario Biagioli [1992] "Employee financial participation in enterprise results in Italy" pp. 50


96. Paolo Emilio Mistrulli [1993] "Debito pubblico, intermediari finanziari e tassi d'interesse: il caso italiano" pp. 30