Regional Wage and Unemployment in Italy: A spatial-temporal analysis

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Abstract

As known, Italy is characterized by a strong polarization between North and South and the 2007 crises has exacerbated such pattern. Some regions have shown a higher degree of resilience, with a fast recovery while others seems to be stacked in a poverty trap. Most of the story is related to the unemployment gap, hence to the regional labour market. The paper investigates upon the functioning of Italian labour market at NUTS 2 level, over 1995-2015, by means of a panel error correction model after controlling for spatial interactions among Italian regions.

Our results show that in the long run wage per worker follows a standard labour demand curve, with a subsequent adjustimento of short run dynamics to the long one. Hence wage are essentially driven by labour productivity. But regional characterics matter, as residuals show a certain degree of cross dependence and presence of common factors. This means that regional disparities could be related to the local functioning of labour market and to productivity gap, that calls for the different industrial and institutional tissue among Italian regions.

Keywords: Regional Labour Market, Resilience, Panel ECM, Cross Dependence

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1 Introduction

Italian labour market is still characterized by a strong trade unions activity, despite several reforms aiming to make more flexible the labour market since

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last decade. The national coverage of unions is the highest in Europe: Italian trade unions have more than 12 million members, perhaps as many as 15 million (Visser, Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts). However, a high proportion of them are retired (almost half - 49% - across the three largest confederations, CGIL, CISL and UIL). Taking this into account, the ICTWSS database of union membership put union density at 37% in 2014. Overall collective bargaining covers 80% of labour market arrangements in 2014.

This makes wage gap rather narrow between Italian regions but at the same time produces large disparities in regional employment (and consequently in unemployment). This because, as in standard new-keynesian labour market models, wage are almost fixed and firms react by adjusting employment to maximize profits. Market clear operates through quantity rather than price adjustment. Indeed, since the well-known North-South dichotomy of Italian industrial tissue, firms in the South react to a higher wage (w.r.t. the competitive one) by reducing employment, and conversely in the North. This is well shown in Fig 1 where we plot the regional unemployment rate: the North vs South polarization is quite clear.

Another way at looking at this picture comes from the comparison of between and within correlations; while wage are strongly correlated everywhere, the unemployment rate appears to be less homogenous between north and south. The picture becomes dramatic when we look at the activity rate, with a lack of correlation between these macro-regions.

These simple stylized facts stresses two important points: the first one relates to the theoretical model we have to identify from data. If markets were efficient, no significant long-run spatial disparities in unemployment at sub-national level would exist, because the equilibrating forces of capital and labour mobility and change in relative prices would eventually eliminate unemployment above frictional levels (Elhorst, 2000). The persistence of unemployment differences, especially between north and south, is mainly due by low flexibility wages and low mobility worker. This points to the literature on non-walrasian labour market characterized by union bargaining, where unions fixes wage in some way (centralized bargaining, monopoly union and so on) and leave to the firms the employment choice along their labour demand cuve. From this point of view this is the "long run" behaviour of the market. The second point stresses the hydiosyncratic components of Italian regions, or regional specific effect in other words, in describing how market adjust to the long run equilibrium (the time dimension of the question). This second point calls for the needs of spatial analysis; as known, regions can be correlated among neighbours and/or to be driven by some common factor. Using a well known thermonology, both strong and weak cross dependence

could be at work.

Summing up, the Italian regional labour market must be analysed along two dimensions: the temporal one, describing short and long run dynamics, and the spatial one, taking into account regional spillovers and common factors. To make more fuzzy this picture, the financial crisis started in 2007 has in some sense exacerbated regional disparities; some regions have showed a higher degree of resilience, aming to recover and to restart, while others have remained trapped in a low development path, increasing the polarization of italian counties.

Such an investigative approach finds evidence in the literature. The principal aim of regional unemployment literature is to investigate the persistence of unemployment and to examine their determinants (Decressin and Fatas, 1995; López-Bazo del Barro and Artis, 2005) using standard statistical methods. Despite these contributions represent a milestone in literature they do not take into consideration some others important factors. As Vega and Elhorst (2016) pointed out the evolution of regional unemployment rates tend to be strongly correlated over time, related to national unemployment rate and correlated across the space. Moreover, numerous empirical studies of the dynamics of unemployment rate are carried out within a linear framework. However, unemployment rate can show nonlinear behaviour as a result of business cycles or some idiosyncratic factors specific to labour market. A review regarding the unit root properties of unemployment is provided by Khraief et al., (2015).

We start from a very simple thoretical model of firm labour demand, widely used in the literature on union models as long run constraint to market equilibrium. The theoretical model is used as a cointegration relationship between wage and unemployment after controlling for unit roots by means of CIPS test. Once estimated and identified the long run equation, it will be used in a panel ECM to estimate efficiently the coefficients, in particular the adjustment coefficient of short to long run dynamics. This steps needs to check for possible cross-dependence among the data by means of the Pesaran CD test and the subsequent CCEMG estimator.

For the reason previously said, we can expect that residuals of the ECM contains still regional hetereogeneity due to the presence of common factors -observed and unobserved- and spatial dependence (Pesaran 2006, 2013). It is important to have a methodology that is able to test both forms of cross-sectional dependence in presence of serial dynamic (Holly et al., 2010, 2011; Bailey et al., 2016, Vega and Elhorst 2016) in order to investigate regional disparities. Our approach follows the methodology developed by Holly et al., (2010) for the house prices. In contrast with Vega and Elhorst (2016) our starting point is a model of labour demand and we will take into

consideration not only the common factor and the cross dependence but also the non-linear behaviour of regional unemployment considering also the long run equilibrium.

The analysis well be carried out for Italian regions NUTS2 for the period 1995-2015 (N=21, T=21), hence before and after the 2007 financial crisis. The emprical investigation allows us to identify a long run relationship between wage and unemployment and the consequent adjustment path. Nonetheless, the dynamics is characterized by local effects due to cross-dependence and common factor. These components are important to explain regional disparities and the different level of resilience among italian regions. If, from one hand, the long run dynamics is characterized by a clear relationship between wage and labour productivity (embodied in the standard labour demand curve), hence by a more flexibile labour market, from the other regional characteristics can affect such a relationship in a dramatic way, leading to increase, rather than to reduce, inequality among Italian territories.

The paper is organized as follows. Section 2 shows some stylized facts. In section 3 we show the theoretical model aiming at identify a long run relationship between wage and unemployment. Section 4 and sub sections show the econometric analysis w.r.t. time, after controlling for unit roots and cross dependence in the data. Section 5 and sub investigates upon the spatial components. Conclusions follow.

2 Stylized Facts

The analysis will be carried out using data from ISTAT (Italian National Institute of Statistic) at regional level for the years 1995-2015. The variables definition is set out in Table A.1 in appendix.

By looking at the data, the regional unemployment rate shown in Figure 1 in the appendix stresses the well-known dichotomy between North and South of Italy where in the North the unemployment rate is lower than in the South.

Regional unemployment is strongly correlated between and within the macro-areas as showed in Table 1. The diagonal elements show the within regional average coefficients and the off-diagonal elements give the between regional average coefficients. Within correlation is higher than between correlation in the Centre and in the South instead there is a strong correlation between North and Centre

Table 2 displays the average of wage correlation coefficient within and between regions. There is a very strong correlation among areas. . This result confirms a centralized bargaining system in Italy. As consequence

	North	Center	South
North	0.79		
Center	0.83	0.82	
South	0.69	0.76	0.82

Table 1: Average of correlation coefficients within and between regions, unemployment rate

wages are not flexible and the labour market adjustments takes place through employment instead than through wages.

	North	Center	South
North	0.99		
Center	0.99	0.99	
South	0.97	0.98	0.99

Table 2: Average of correlation coefficients within and between regions, log per ULA wage.

Table 3 shows average of correlation coefficient within and between regions of the activity rate. The results show a strong correlation within areas in the North and in the Centre. Nevertheless, the within correlation in the Southern regions is low. This result underlines a difference not only between macro-areas but also among Southern regions. Finally, there is no correlation between South and the other areas. The result reinforces the fact that Italy is characterized by a North South divide.

	North	Center	South
North	0.81		
Center	0.86	0.90	
South	0.01	-0.01	0.47

Table 3: Average of correlation coefficients within and between regions, Activity Rate.

Tab14 (appendix) shows in details correlations between regions and Tab.15 show cross correlation matrix.

Finally Tab. 4 show factor loading for regional unemployment. Roughly, factor loading measure how national unemployment affects the regional one; when estimated coefficient is higher (lower) than one this means that the single region reacts more (less) than the national one. Estimating factor

loading is a debate question as involves specific as well as common factors, see the contribution of Elhorst 2016 for further details. Tab. 4 shows two different approaches. In col. (a) the two-steps Elhorst approach is used: it is based on controlling for spatial components and cross-dependence. Col. (b) provide a naive estimates by OLS on the unemployment rate. What is striking is that by comparing cols (a) and (b) differences are very low, at meaning tha spatial components in Italy could be not so dramatic. We will come back on the point later.

Region		
	(a)	(b)
Pie	1.09	1.14
Val	0.75	0.79
Lig	1.16	1.18
Lom	0.64	0.67
Bolz	0.23	0.25
Tren	0.72	0.73
Ven	0.64	0.65
FVG	0.74	0.76
ER	0.69	0.74
Tos	0.76	0.77
Umb	0.98	1.04
Mar	0.83	0.85
Laz	0.93	0.98
Abr	1.05	1.08
Mol	0.95	1.03
Cam	1.54	1.63
Pug	1.31	1.4
Bas	0.8	0.87
Cal	1.62	1.72
Sic	1.69	1.71
Sard	0.96	1.01

Table 4: Factor loading: (a) Elhorst two-steps (2016), (b) RU.

3 The walrasian labour demand curve

As it well known, the microeconomic theory for labour demand curve is based on the simple equality between real wage rate w and labour marginal productivity $F'_L(K, L)$:

$$w = F'(L) \tag{1}$$

where L is the quantity of labour maximizing firm profit in a market economy. In order to make this equation viable for an econometric approach, it is common to assume that the production function $F(K, L)$ has a standard Cobb-Douglas form: $F(K, L) = K^\beta L^\alpha$ where α and β are the capital and wage share respectively (moreover with constant returns to scale $\alpha + \beta = 1$). By taking the capital input as a constant C, the labour marginal productivity is simply $F'(L) = \frac{\partial F}{\partial L} = \alpha C L^{-(1-\alpha)}$ so as eq.1 becomes $w = \alpha C L^{-(1-\alpha)}$. By taking logs in both sides we finally obtain:

$$\log(w) = C1 - (1 - \alpha) \log(L) \tag{2}$$

with $C1 = \log(\alpha C)$. However, for the sake of scale, it is preferable to measure labour in employment rate: $l = L/LF$, where LF is the labour force.. Eq.2 becomes:

$$\log(w) = C2 - (1 - \alpha) \log(l) \tag{3}$$

with $l = (1 - u)$,where u is the unemployment rate, and $C2 = C1 - (1 - \alpha) \log(LF)$.

Eq. 3 represents the equilibrium labour demand for a large variety of approaches, both in walrasian and non-walrasian approaches, (bargaining models, efficiecny wage, unions behaviour and so on, see Blanchard and Fisher for a review). For such a reason we are going to adopt eq.3 as our long run constraint (cointegration term) in the Error Correction Model provided in sec 4.

Nevertheless, in order to identify properly eq. 3 as a cointegration relationship between wage and unemployment in the panel ECM model, we must provide an economic assumption on α. In the Johanseen approach to cointegration in VAR models (see Johansen 1988), this is done by means of an unrestricted estimate of the long run equation, providing a rough estimate of α, and then a second step involving a test of linear restrictions on α based on the economic assumption made a-priori. If the test is succesfull, the long run equation is properly identified.

Our a priori assumption on α comes from real data of wage share in Italy over 1950-2016. Data are in figure 2 in the appendix:

As Fig?? shows, the average wage share in the last 66 years is around 0.60 for the total economy; this means that $(1-\alpha) = 0.4$.The restricted cointegration relationship Eq.3 finally is:

$$\log(w) = C2 - 0.4 \log(1-u) \tag{4}$$

Eq. 4 will be used as long run constraint in the ECM in section 4.

4 Econometric approach: time analysis[1]

As previously underlined regional unemployment time series can be characterized by correlation over time and heterogeneity generated by the presence of common factors and spatial dependence. Non-stationarity underlines path dependency (Mitchell 1993) while cross-dependency can depend on unobserved common components (Pesaran 2006). Do not take into consideration cross-dependency can give, as result, bias estimations (Pesaran 2006, 2007, 2015). In order to investigate the presence of unit roots and cross dependency for Italian unemployment series we are going to test for cross dependency using the CD test. Moreover, a CIPS test for units roots in presence of cross-dependency will be applied. Furthermore, in presence of unit roots in unemployment series a cointegration relationship will be investigated. Finally, an Error Correction Model (ECM) will be presented.

4.1 CD Test

One major issue that inherently arises in every panel data study with potential implications on parameter estimation and inference is the possibility that the individual units are interdependent. Nevertheless, it is typically assumed that disturbances in panel data models are cross-sectionally independent. Modelling general forms of cross-sectional dependence is not a straightforward task. To deal with this issue, the panel data literature has mainly adopted two different approaches to modelling error cross-sectional dependence, the spatial approach and the factor structure approach. Spatial models were developed primarily for cross-sectional data using a concept of a distance metric, which allowed formulating models with a structure similar to that provided by the time index in time series. The factor structure approach assumes the presence of an unobserved common component in the disturbance which is a linear combination of a fixed number of factors.

[1] The statistical analysis, both in time and in space, has been developed by R. We wish to thank Giovanni Millo for valuable aid in coding. Usual disclaimers apply.

In accordance with this approach Pesaran (2006) proposed a common correlated effect estimator (CCE) which asymptotically eliminates strong and weak forms of cross sectional dependence in large panels. Moreover, CCE estimator has the advantage that does not require estimating the number of latent factors. In order to test for cross dependence in this paper we will use a CD (cross-dependence) test of error cross dependence which does not require a priori specification of a connection matrix and is applicable to a variety of panel data models, including stationary and unit roots dynamic heterogeneous panel with structural breaks, with short T and large N (Pesaran 2004). The CD test is based on an average of the pair-wise correlations of the OLS residuals from the individual regressions in the panel and tends to a standard normal distribution as $N(0,1)$ under the null hypothesis of no error cross-sectional dependence.

Genarally speaking, the Pesaran CD test is the following:

$$CD = \sqrt{\frac{N}{(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}\right)$$

where $\widehat{\rho}_{ij}$is the sample estimate of the pair-wise correlation of the residuals coming from the estimates under hypothesis:

$$\widehat{\rho}_{ij} = \widehat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\hat{u}_{jt}}{\left(\sum_{t=1}^{T}\hat{u}_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T}\hat{u}_{jt}^2\right)^{1/2}}$$

As in HYP,, we perform CD test on the residuals of the ADF test on single series RW and RU, in order to investigate whether standard unit roots test are affected by cross-dependence. In such a case it is known that tests like IPS or other tests are no longer valid. With cross-dependence, Pesaran 2007 suggests to filter out the cross-sectional dependence by augmenting the ADF regressions with cross section averages.The panel unit root test proposed by Pesaran (known as the CIPS test) is based on cross section augmented ADF (CADF) regressions, carried out separately for each State.

Results of ADF test on the first $p = 4$ lags and CD tests on residuals of the ADF test are shown in tables 5 and 6 respectively.

Table 5 shows the residual cross correlation of ADF (p) regression for regional real wage and regional unemployment. The values in the table are the simple average of the pair-wise cross section correlation coefficient of the ADF(p) regression residual. For each p=1,2,3,4 the average sample estimates of the pair-wise correlation of the residual $\bar{\rho}$ has been computed. For regional unemployment and regional wage $\bar{\rho}$ is estimated to be around 50%,

Average Cross Correlation ρ

	ADF(1)	ADF(2)	ADF(3)	ADF(4)
RU	0.525	0.522	0.540	0.422
RW2	0.558	0.531	0.232	0.210

Table 5: Residual cross-correlation of ADF(p) regressions: average correlation coefficients .Notes: pth-order Augmented Dickey Fuller test statistics, ADF(p), are computed for each cross section unit separately. The values in 'average cross correlation coefficients' are the simple average of the pair-wise cross section correlation coefficients of the ADF(p) regression residuals $\bar{\rho} = [2/N(N-1)] \sum_{i=1}^{N-1} \sum_{j=1+1}^{N} \rho_{ij}$, with ρ_{ij} being the correlation coefficient of the ADF(p) regression residuals between ith and jth cross section units.

CD Test

	ADF(1)	ADF(2)	ADF(3)	ADF(4)
RU	33.14	32.11	32.25	24.44
RW2	35.27	32.67	13.85	12.18

Table 6: Residual cross-correlation of ADF(p) regressions: CD test statistics. $CD = \sqrt{2T/(N-(N-1))} \sum_{i=1}^{N-1} \sum_{j=1+1}^{N} \rho_{ij}$ which tends to $N(0,1)$ under the null hypothesis of no error cross-sectional dependence.

As tab. 6 clearly shows there is a strong presence of cross dependence in the ADF residuals. This means that standard unit root tests are highly biased and that the CIPS test is strongly adivsed.

4.2 Panel Unit Roots test

Over the last few years there has been a lot of research on non-stationary panel with large cross section and time series dimension especially in the context of testing the presence of unit roots. The first generation of panel unit root tests (PURTs) (Levin and Lin, 1992 –pooled ADF test, Im Pesaran and Shin, 1997 –IPS test-¸Maddala and Wu, 1999 –Fisher combination test, MW-) has, as a common feature, restriction that cross-sections are independent (under this assumption various central limit theorems can be applied to obtain test statistics with an asymptotic normal distribution Moon and Peron 2004). Moreover, all the tests differ only in the way the information is pooled. Nevertheless, simple pooling is valid only if the units of the panel are independent from each other and they are sufficient homogeneous. The second

generation of PURTs takes into consideration the cross dependency. Following a factor structure approach several panel unit roots tests in presence of cross dependency has been proposed. The first one (Pesaran 2007), suggest a cross-sectionally augmented Dickey-Fuller (CADF) test where the standard DF regressions are augmented with cross sectional averages of lagged levels and first differences in the individual series. He also considers a cross sectional augmented IPS, CIPS test, which is the sample average of the individual CADF test. A second panel unit root test has been proposed by Moon and Perron (2004). To model cross-sectional dependency they consider an approximate linear dynamic factor model in which the panel data is generated by idiosyncratic shock and unobservable dynamic factors that are common to all the individual units but to which each individual reacts heterogeneously. In order to take into consideration cross dependency Moon and Peron proposed a test that uses de-factored panel data obtained by projecting the panel data to the space orthogonal to the factor loading. To estimate the matrix of factor loading they use a modified version of principal component method used in Stock e Watson (1998) and Bai and Ng (2000, 2001). The test proposed by Moon and Perron is developed for dynamic panel data model with fixed effect.
A third type of panel unit root test has been proposed by Bai and Ng (2004). They develop a methodology that make use of the factor structure of large dimensional panels to understand the nature of non-stationarity in the data. The methodology is named PANIC –Panel Analysis of Non-stationarity in Idiosyncratic and Common components. PANIC detect whether the non-stationarity in a series is pervasive, variable specific or both. Moreover, it can determine the number of independent stochastic trend driving the common factors. It also permits valid pooling of individual statistic and thus panel test can be constructed. Moreover, a distinctive feature of panic is that it tests the unobserved component of the data instead of the observed series. The key to panic is consistent estimation of the space spanned by the unobserved common factor and the idiosyncratic errors without knowing a priori whether these are stationary or integrated process (Bai and Ng 2004). In order to test for panel unit roots in presence of cross-sectional dependence we will follow the approach proposed by Pesaran (2007). The Pesaran CIPS test is the following.

Let z_{it} the observation on i-th cross-section unit at time t generated according to a dynamic linear heterogeneous panel data model:

$$z_{it} = (1 - \phi_i)\,\mu_i + \phi z_{i,t-1} + \varepsilon_{it} \tag{5}$$

Where ε_{it} has a single factor structure:

$$\varepsilon_{it} = \gamma_i f_t + e_{it} \tag{6}$$

where f_t is the unobserved common effect, $f_t \sim$i.i.d.$\left(0;\sigma_f^2\right)$, and γ_i is the individual factor loading, $\gamma_i \sim$i.i.d.$\left(0;\sigma_\gamma^2\right)$ and e_{it} is the individual specific error it can be i.i.d.$(0;\sigma_i^2)$or, more generally, a stationary autoregressive process. Rearranging 5 and 6 we obtain:

$$\Delta z_{it} = \alpha_i + \beta_i z_{it-1} + \gamma_i f_t + e_{it} \tag{7}$$

where $\alpha_i = (1-\phi_i)\,\mu_i$; $\beta_i = -(1-\phi_i)$ and $\Delta z_{it} = z_{it} - z_{i,t-1}$ where $H_0 : \beta_i = 0 \,\forall\, i$ against the possibility heterogeneous alternatives $H_1 : \beta_i < 0 \; i = 1 \ldots N_t$ $\beta_i = 0 \; i = N_1 + 1,\; N_1 + 2 \ldots\ldots.N$.
Let $\overline{\gamma}_t = \sum_{j=1}^{N} \gamma_y / N$ and, in accordance with Pesaran (2006), the common factor f$_t$ can be proxied by the cross section mean of z_{it} $\overline{Z}_t = \sum_{j=1}^{N} Z_y/N$ ad its lagged values $\overline{z}_{t-1}$, $\overline{z}_{t-2}\ldots$
The test for the null of units root hypothesis Pesaran (2007) uses the t ratio of the OLS estimates of b$_i$ in the cross-sectionally augmented Dickey-Fuller (CADF) regression.

$$\Delta z_{it} = a_i + b_i z_{i,t-1} + c_i \overline{z}_{t-1} + d_i \Delta \overline{z}_t + e_{it} \tag{8}$$

The CIPS test is the following:

$$CIPS\,(N,T) = \frac{\sum_{i=1}^{N} t_i\,(N,T)}{N} \tag{9}$$

where t$_i$(N,T) is the cross-sectionally augmented Dickey–Fuller statistic for the i-th cross-section
unit given by the t-ratio of the coefficient of $z_{i,t-1}$ in the CADF regression defined by (8). The distribution of the test is not standard and the critical value are tabulate by the author for different combination of N and T and are given in Tables (a)-(c) in Pesaran (2007).

Table 7 shows results of Cips test with an intercept while tab.8 shows same results but with a linear trend assumption.

The critical values for the CIPS test are given in tables (a)-(c) in Pesaran 2007. In presence of intercept 5% and 10% critical values for rejection of the unit root hypothesis are, respectively, -2.11 and -2.03. In presence of intercept and linear trend 5% and 10% critical values for rejection of the unit root hypothesis are, respectively, -2.62 and -2.54. The test confirms the unit roots presence.

Pesaran CIPS test panel unit roots test

	CADF(1)	CADF(2)	CADF(3)	CADF(4)
Δ((RU))	-3.19	-2.12	-2.00	-1.75
Δ(log(RW2))	-3.03	-2.50	-2.07	-1.61
RU	-1.87	-1.70	-1.82	-1.62
RW2	-1.95	-2.54	-2.02	-1.93

Table 7: Pesaran's CIPS panel unit root test results: with an intercept). 5 percent and 10 percent critical values for rejection of the unit root hypothesis are, respectively, -2.21 and -2.10.

With an intercept and linear trend

	CADF(1)	CADF(2)	CADF(3)	CADF(4)
RU	-2.41	-2.22	-2.32	-1.58
RW2	-1.88	-2.52	-2.11	-1.78

Table 8: Pesaran's CIPS panel unit root test results: with an intercept and a linear trend. 5 percent and 10 percent critical values for rejection of the unit root hypothesis are, respectively, -2.73 and -2.63.

The results show that the null hypothesis (H0 hypothesis presence of unit root) cannot be rejected in both series RW (regional real per capita wage) and RU (regional rate of unemployment). We will consider these series as I(1). The results are also in line with the raw data previously discussed and confirm that Italian labour market is characterized by path dependency and common factor. In order to remove unit roots we will investigate a cointegration relationship between RW and RU in order to find a long run relationship between them in accordance with the theoretical labour demand curve of section 3. Next section is devoted to this analysis.

4.3 Cointegration and PECM model

Applying the CD test and the CIPS test we found out that regional per capita wage and regional unemployment rate are characterized by cross dependency and unit roots. The series are integrated of order I(1). Cointegration implies that the two integrated series never drift far apart from each other, that is they maintain an equilibrium. The Panel Error Correction Model (ECM) is the preferred method for estimation when two integrated time series are statistically related or cointegrated and it offers the important benefit to allowing estimation of both short and long term effect.

We start by performing a cips test on the residuals of the long run equation in the unrestricted version, i.e. withour a-priori assumption on the coefficient of $\log(1-u)$.

$$\log(w)_{it} = \hat{\alpha}_i + \hat{\beta}_i \log(1-u)_{it} + \varepsilon_{it} \tag{10}$$

with

$$\varepsilon_{it} = \sum_{l=1}^{m} \gamma_{il} f_{lt} + \upsilon_{it}$$

where f_{it} are the common factors and γ_{il} the factor loading.

In order to estimate the coefficient $\hat{\beta}_i$ we have to take into consideration the presence of cross sectional dependence due the common factor. Early panel data literature assumed cross-sectional independent errors and slope homogeneity, moreover, heterogeneity across units was modelled by using unit-specific intercepts only, treated as fixed or random. Cross-sectional error dependence was only considered in spatial models, but not in standard panels. Conventional panel estimators such as fixed or random effects can result misleading inference and even inconsistent estimators, depending on the extent of cross-sectional dependence and on whether the source generating the cross-sectional dependence (such as an unobserved common shocks) is correlated with regressors. In order to take into consideration cross dependency Pesaran (2006) suggested the Common Correlated Effect (CCE) estimator (Pesaran 2006, Kapetanios, Pesaran and Yagamata 2011, Pesaran and Tosetti 2011, Chudik, Pesaran and Tosetti 2011). CCE consists of approximating the linear combinations of the unobserved factors by cross section averages of the dependent and explanatory variables, and then running standard panel regressions augmented with these cross section averages. Both pooled and mean group versions are proposed, depending on the assumption regarding the slope homogeneity.

According, we proved altenative estimators to eq. 4, namely the Mean Group (MG), that does not control for cross-dependence and common factors in the residuals, the Common Correlated Effect (CCE) estimator, that augments estimates with cross section averages. CCE estimates are then averaged over the individual coefficients α_i and β_i to obatin the Common Correlated Effect Mean Group (CCEMG) estimates. Instead, by assuming homogeneity of CCE estimates of $\beta_i = \beta$ we obtain the Common Correlated Effect Pooled (CCEP) (see Pesaran 2006).

To gain additional explicative power to eq. 10 we add a second covariate controlling for the activity rate. Estimates results are in tab. 9

	MG	CCEMG	CCEP
Intercept	0.60	-0.00	
se	0.68	0.14	
log(1-u)	0.20	-0.47	-0.43
se.1	0.41	0.12	0.16
tasso.att	0.04	-0.00	-0.00
se.2	0.01	0.00	0.00
avg.rho	0.36	-0.03	-0.04
CD-test	23.63	-2.18	-2.79

Table 9: Estimation result for cointegration equation

Table 9 reports the mean group estimator (MG), the Common Correlated Effect Mean Group (CCEMG) and the Common Correlated Effect Pooled (CCEP). MG estimator doesn't take into account the cross-sectional dependence and common factors in the residuals because it is obtained simply running OLS regression. The CCE estimator, by contrast, takes cross-sectional dependence and common factor into consideration (Pesaran 2006). Moreover, the CCEMG estimator is a simple average of the individual CCE estimators and the CCEP is obtained under the assumption that individual slope β_i are the same (Pesaran 2006).

As expected the MG estimates are dramatically different from CCEMG and CCEP. The CD test for the CCEMG has a p-value of 3% meaning that cross-dependence is not totally erased at 5% of significance. Estimates are correct in sign and magnitude with the a priori hypothesis of $\beta = -0.4$. The Wald test confirms such assumption as provides $\chi^2 = 0.347$. The presence of cross dependency generates biased estimators (MG). In order to take into consideration cross-dependence we used, as coefficient of the long run equation, the ones obtained using the CCEMG. The result confirms the appropriateness of using the CCEMG as coefficient of the long run equation.

In order to check that eq. $\log(w)_{it} = -0.4 \log(1-u)_{it} + \epsilon_{it}$ is effectively the long run equation, we have to test for unit root in the residuals by means of the CIPS test on $\epsilon_{it} = \log(w)_{it} + 0.4 \log(1-u)_{it}$. Results are in tab. 10

CIPS(1)	CIPS(2)	CIPS(3)	CIPS(4)
-1.70	-2.32	-2.16	-2.08

Table 10: CIPS test. 1 percent and 5 percent critical values for rejection of the unit root hypothesis are, respectively, -2.21 and -2.10.

The null hypoteshis of unit root is rejected for $p = 2$.

Once identified the long run equation, the next step is to plug it into a Panel Error Correction Model, to investigate upon the dynamics of wage and unemployment:

$$\Delta logRW2_{it} = \alpha_i + \phi_i \left(logRW2_{it-1} + 0.4 \log(1 - u_{t-1}) \right) + \delta_{1i} \Delta \log RW2_{\ i,t-1} \tag{11}$$

$$+\delta_{2i} \Delta tassoatt_{it} + \delta_{3i} \Delta logRU_{\ it-1} + \upsilon_{it} \tag{12}$$

The coefficient ϕ_i measures the speed of adjustment of the per-capita wage to the shock. To allow for possible cross-sectional dependence in the error υ_{it} we compute CCEMG and CCEP estimators of the parameters, as well as the MG estimators that do not take into consideration cross-sectional dependence The results are showed in Table 11

	MG	CCEMG	CCEP
lag(LongRun)	-0.046	-0.451	-0.296
se	0.007	0.077	0.083
diff(lag(log(RW2)))	-0.029	0.108	0.025
se	0.033	0.073	0.071
diff(lag(log(RU)))	-0.038	0.006	-0.003
se	0.008	0.009	0.007
diff(tasso.att)	-0.007	-0.003	-0.001
se	0.002	0.001	0.001
half-life	14.719	1.156	1.975
R2	0.150	0.650	0.650
avg rho	0.429	-0.031	-0.042
CD test	27.080	-1.980	-2.680

Table 11: Panel Error Correction Model

Once again, the CCEMG provides the best estimates, as CD test is barely on 5% of significance. The adjustment coefficient ϕ is correctly negative, meaning that the short run dynamics adjusts to the long run one. The time for 50% of adjustment (half life) is rather fast, 1.16 years, dramatically faster than the MG estimates, about 15 years. About results, the short run dynamics seems to be mainly driven by the activity rate, being the only significative variable. This confirms the crucial role of this variable in capturing not only economic rationale but the strong polarization of Italian regions.

5 Econometric analysis: The space investigation

The previous analysis provided a consistent estimate of the cointegration relationship between wages and unemployment. Cross dependency can be generated by common factors described by equation 6 and the remaining idiosyncratic components ε_{it} that capture weak dependence in the overall residuals, υ_{it}. These idiosyncratic factors reflect forms of local dependence that are spatial in nature. Spatial patterns will be based on the estimation of spatial weight matrix that is commonly used in the literature. To investigate possible spatial patterns in the residuals of long run equation 10, following HPY , the residual are decomposed in two components: m common factors and spatial autocorrelation:

$$\varepsilon_{it} = \sum_{j=1}^{m} \gamma_{im} f_{mt} + \upsilon_{it} \tag{13}$$

where f_{mt}, $m = 1, 2..$ are the common factors and γ_{im} are the associated factor loadings. We experimented with different values of $m = \{1, 2, 3\}$ and estimated the factors by the principle components. The idiosyncratic components, υ_{it} are then computed as residuals from the OLS regressions of ε_{it} on the estimated factors over for each i.

To investigate the strength of spatial dependence in the idiosyncratic components, for each m we estimated the following standard spatial lag model (SAR) in υ_{it}:

$$\upsilon_{it} = \lambda \sum_{j=1}^{n} s_{ij} \upsilon_{jt} + \omega_{it} \tag{14}$$

where λ is a spatial autoregressive parameter, and s_{ij} is the generic element of the N x N spatial weight matrix S, and $\omega_{it} \sim n.i.i.d.(0, \sigma_{\omega}^2)$.

Log-likelihood of eq.14 is provided by Anselin (198?). For S, following the approach of Anselin, we used a contiguity criterion and assigned $s_{ij} = 1$ when Region i and j share a common border or vertex, and $s_{ij} = 0$ otherwise. It is worth stressing that Sicily and Sardinia, being islands, do not share any border but, by looking at transportation data, they are connected to Calabria and Lazio respectively. The connectivity map is given in Fig. 3

5.1 Principal Components

We start by extracting principal components (common factors) from ϵ_{it}, fixing $m = 3$. The scree plot is given in Fig.4 in the appendix and it crearly shows that $m = 1$.According, italian regions share just one common factor among them.

5.2 SAR analysis

As previously said, we use factors to estimate residuals of eq.13 by running OLS for each i. Then the SAR model is applied to them. Results are in tables 12 and 13 for non standard and standardized case respectively. We show $m = 3$ results but the analysis should consider just $m = 1$.

	m=1	m=2	m=3
λ	0.483	-0.267	-0.349
analytical SE	0.042	0.057	0.056
λ ML	0.483	-0.267	-0.349
numerical SE	0.039	0.056	0.058

Table 12: Estimates of spatial autocorrelation in defactored residuals

	m=1	m=2	m=3
λ	0.416	-0.288	-0.401
analytical SE	0.045	0.057	0.055
λ ML	0.416	-0.288	-0.401
numerical SE	0.043	0.058	0.057

Table 13: Estimates of spatial autocorrelation in standardized defactored residuals.

Results show that spatial correlation among italian region is not remarkable, although statistical significative. A results that we expect by raw data. As in HPY we also checked the spatial estimates to see if they are robust to possible differences in the error variances across the regions, by estimating the spatial model using standardized residuals. Differences however are not sensible.

6 Conclusion

This paper has explored the empirical functioning of regional labour market in Italy by means of a panel data model based on 21 Italian regions for 21

years. Starting from some stylized facts showing how wage per worker is highly correlated among Italy - beacause of unions - while unemployment are less - as a consequence of wage rigidity - we focus on the relationship between log wage per worker and the unemployment rate, aiming at describing labour demand. Labour market functioning could provide a rationale to the strong polarization that data shows, notably between north and south of Italy. Moreover, as our data covers 1995 2015, we investigate how 2007 financial crisis has affected regional labour market, hence living standard. Indeed, data show that some regions, notably in the North, were able to react and to recover fast to the shock, while most part of the south did not; this has got worse regional disparities. Indirectly, this means that some Italian regions show a higher degree of resilience.

In order to provide efficient estimates we control both for unit root and cross-dependence in the data. This allowed us to test for the presence of a long run relationship and consequently to investigate upon the adjustment path by means of a panel Error Correction Model. Finally, following Holly et al. 2016, we performed test for the presence of common factor and spatial autocorrelation in the residuals of the ECM.

The data show that a long relationship does exist; this has been identified by means of a simple theoretical model of labour demand. Moreover cross dependence and common factor are presents in the residuals of the ECM, leading us to conclude that regional specific effects are at work.

Summing up, despite a strong union activity in the Italian labour market, the short run dynamics, driven basically by the activity rate adjust to a long run relationship driven by labour productivity. Nonetheless this dynamics embodies local effects due to spatial correlation, although not in a severe way.

From a policy point of view, the crisis of the South of Italy, with a dramatically high unemployment rate, especially for young workers, calls for increasing labour productivity in a more flexibile setting. This means basically to increase firms efficiency, even in the organization and management, and fostering human capital; in the short run activity rate do play an important role. The presence of regional spillovers triggers a sort of "contagious" that, if properly addressed, could be beneficial.

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8 Appendix

Table A.1 Variables definitions - Source: ISTAT

Table A.1	
Unenployment	Someone aged 16 to 74 without work during the reference week; available to start work within the next two weeks (or has already found a job to start within the next three months); actively having sought employment at some time during the last four weeks.The unemployment rate is the number of people unemployed as a percentage of the labour force.
Wage	**Wage** is the remuneration in cash paid by the employer before tax deductions and social security contributions payable by wage-earners and retained by the employer.
ULA/AWU	One **annual work unit**, abbreviated as **AWU**, corresponds to the work performed by one person who is occupied on a full-time basis. Full-time means the minimum hours required by the relevant national provisions governing contracts of employment.
Activity rate	**Activity rate** is the percentage of active persons in relation to the comparable total population. The economically active population comprises employed and unemployed persons.

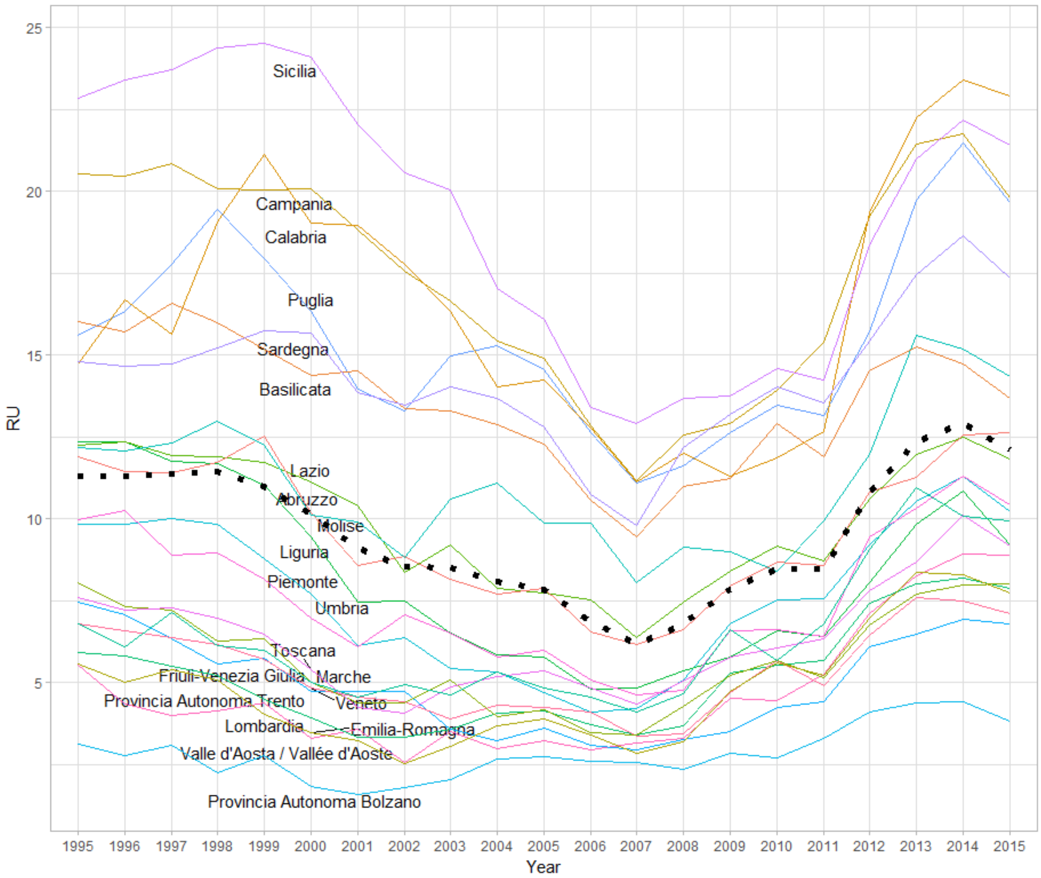

Figure 1: Regional vs National (dashed) umployment rate

Table 14: Cross correlation coefficients Unemployment rate vs Activity rate

	Pie	Val	Lig	Lom	Bolz	Tren	Ven	FVG	ER	Tos	Umb	Mar	Laz	Abr	Mol	Cam	Pug	Bas	Cal	Sic	Sard
Pie	-0.04	0.22	0.02	-0.23	-0.11	0.26	-0.32	-0.16	-0.37	-0.04	-0.03	-0.23	-0.16	0.13	-0.49	0.07	0.01	-0.33	-0.24	-0.19	-0.26
Val	0.54	0.50	0.49	0.41	0.48	0.60	0.29	0.44	0.22	0.57	0.47	0.39	0.46	-0.12	-0.36	-0.34	0.24	-0.26	-0.34	-0.56	0.20
Lig	-0.49	-0.05	-0.39	-0.63	-0.55	-0.07	-0.70	-0.56	-0.70	-0.45	-0.37	-0.62	-0.58	0.33	-0.35	0.46	-0.07	-0.20	0.03	0.18	-0.55
Lom	0.43	0.32	0.34	0.29	0.41	0.43	0.16	0.28	0.06	0.41	0.28	0.25	0.36	-0.18	-0.52	-0.35	0.05	-0.43	-0.47	-0.62	0.02
Bolz	0.53	0.21	0.36	0.45	0.57	0.35	0.32	0.38	0.21	0.50	0.31	0.40	0.51	-0.31	-0.44	-0.46	0.03	-0.47	-0.49	-0.75	0.09
Tren	-0.16	0.21	-0.12	-0.34	-0.25	0.15	-0.43	-0.25	-0.47	-0.15	-0.10	-0.33	-0.29	0.32	-0.40	0.22	-0.02	-0.27	-0.10	-0.08	-0.32
Ven	0.04	0.21	0.04	-0.11	0.00	0.24	-0.23	-0.08	-0.30	0.05	0.00	-0.13	-0.04	0.03	-0.54	0.01	-0.01	-0.36	-0.26	-0.29	-0.24
FVG	-0.02	0.16	-0.03	-0.18	-0.07	0.20	-0.30	-0.14	-0.36	-0.01	-0.04	-0.19	-0.10	0.08	-0.49	0.03	-0.05	-0.35	-0.30	-0.28	-0.29
ER	0.44	0.33	0.35	0.31	0.43	0.44	0.19	0.29	0.08	0.43	0.29	0.26	0.38	-0.22	-0.52	-0.35	0.06	-0.40	-0.46	-0.61	0.03
Tos	0.26	0.22	0.19	0.13	0.23	0.34	-0.01	0.11	-0.10	0.28	0.17	0.09	0.21	-0.13	-0.46	-0.18	0.08	-0.35	-0.38	-0.49	-0.11
Umb	-0.02	0.23	-0.02	-0.16	-0.08	0.24	-0.29	-0.13	-0.33	0.01	-0.03	-0.16	-0.11	0.19	-0.43	0.16	0.09	-0.25	-0.11	-0.17	-0.24
Mar	0.47	0.43	0.40	0.34	0.44	0.52	0.22	0.34	0.16	0.48	0.36	0.32	0.39	-0.10	-0.39	-0.27	0.20	-0.28	-0.34	-0.53	0.12
Laz	-0.26	0.15	-0.18	-0.43	-0.35	0.18	-0.49	-0.34	-0.51	-0.22	-0.16	-0.41	-0.37	0.28	-0.37	0.34	0.06	-0.13	0.01	0.10	-0.35
Abr	-0.17	0.17	-0.09	-0.34	-0.27	0.22	-0.42	-0.28	-0.44	-0.13	-0.08	-0.32	-0.29	0.25	-0.39	0.29	0.13	-0.12	-0.00	0.05	-0.24
Mol	0.08	0.19	0.02	0.00	0.05	0.30	-0.13	-0.02	-0.15	0.16	0.05	-0.02	0.04	0.08	-0.24	0.19	0.31	-0.07	0.01	-0.17	-0.13
Cam	-0.26	0.24	-0.20	-0.42	-0.37	0.21	-0.46	-0.33	-0.44	-0.21	-0.15	-0.37	-0.39	0.45	-0.26	0.52	0.23	0.06	0.24	0.25	-0.22
Pug	-0.01	0.21	-0.00	-0.11	-0.07	0.33	-0.22	-0.12	-0.22	0.07	0.02	-0.11	-0.07	0.10	-0.28	0.30	0.37	0.06	0.10	0.03	-0.11
Bas	-0.48	0.02	-0.40	-0.61	-0.53	-0.04	-0.63	-0.55	-0.63	-0.45	-0.40	-0.57	-0.56	0.42	-0.31	0.57	0.02	-0.05	0.19	0.31	-0.39
Cal	0.12	0.54	0.22	-0.01	-0.03	0.59	-0.04	0.10	0.02	0.22	0.30	0.06	-0.02	0.43	-0.03	0.39	0.64	0.32	0.39	0.24	0.20
Sic	-0.51	0.12	-0.37	-0.63	-0.63	0.06	-0.65	-0.53	-0.58	-0.43	-0.29	-0.56	-0.62	0.55	-0.09	0.73	0.24	0.23	0.43	0.54	-0.32
Sard	0.16	0.42	0.19	-0.01	0.05	0.53	-0.08	0.04	-0.09	0.20	0.20	0.03	0.05	0.13	-0.34	0.16	0.36	0.03	0.03	-0.05	0.08

Table 15: Cross correlation coefficients Unemployment rate vs log Wage per employed

	Pie	Val	Lig	Lom	Bolz	Tren	Ven	FVG	ER	Tos	Umb	Mar	Laz	Abr	Mol	Cam	Pug	Bas	Cal	Sic	Sard
Pie	-0.07	-0.22	-0.11	-0.05	-0.04	-0.08	-0.05	-0.10	-0.04	-0.11	-0.11	-0.09	-0.13	-0.18	-0.45	-0.19	-0.21	-0.29	-0.28	-0.26	-0.23
Val	0.51	0.38	0.48	0.53	0.54	0.50	0.53	0.48	0.53	0.48	0.46	0.50	0.45	0.42	0.15	0.41	0.38	0.31	0.31	0.35	0.37
Lig	-0.52	-0.65	-0.56	-0.51	-0.50	-0.54	-0.51	-0.55	-0.50	-0.56	-0.56	-0.54	-0.58	-0.61	-0.80	-0.62	-0.64	-0.70	-0.68	-0.68	-0.65
Lom	0.42	0.30	0.40	0.45	0.46	0.43	0.44	0.41	0.45	0.40	0.39	0.41	0.37	0.33	0.05	0.33	0.31	0.22	0.23	0.26	0.28
Bolz	0.53	0.45	0.53	0.57	0.58	0.56	0.56	0.55	0.58	0.54	0.52	0.53	0.51	0.48	0.24	0.49	0.47	0.38	0.40	0.43	0.45
Tren	-0.22	-0.36	-0.26	-0.20	-0.18	-0.23	-0.20	-0.24	-0.19	-0.26	-0.27	-0.23	-0.28	-0.33	-0.58	-0.33	-0.36	-0.43	-0.42	-0.39	-0.37
Ven	0.02	-0.11	-0.01	0.05	0.06	0.02	0.04	0.01	0.05	-0.01	-0.02	0.00	-0.04	-0.09	-0.35	-0.09	-0.11	-0.19	-0.19	-0.16	-0.13
FVG	-0.05	-0.18	-0.07	-0.02	-0.01	-0.05	-0.02	-0.06	-0.02	-0.08	-0.08	-0.06	-0.09	-0.15	-0.41	-0.15	-0.18	-0.25	-0.24	-0.22	-0.20
ER	0.43	0.31	0.41	0.46	0.47	0.44	0.46	0.43	0.47	0.41	0.40	0.42	0.39	0.34	0.07	0.34	0.33	0.24	0.24	0.27	0.30
Tos	0.24	0.11	0.22	0.27	0.28	0.24	0.26	0.23	0.28	0.22	0.20	0.23	0.19	0.15	-0.12	0.15	0.12	0.04	0.05	0.07	0.10
Umb	-0.07	-0.20	-0.10	-0.05	-0.03	-0.08	-0.05	-0.09	-0.04	-0.11	-0.12	-0.08	-0.13	-0.17	-0.43	-0.19	-0.20	-0.27	-0.27	-0.24	-0.22
Mar	0.45	0.33	0.42	0.47	0.48	0.44	0.46	0.43	0.47	0.42	0.40	0.44	0.39	0.35	0.08	0.34	0.33	0.25	0.25	0.29	0.31
Laz	-0.31	-0.45	-0.36	-0.30	-0.29	-0.34	-0.30	-0.35	-0.30	-0.36	-0.36	-0.32	-0.38	-0.42	-0.64	-0.43	-0.45	-0.52	-0.51	-0.49	-0.46
Abr	-0.22	-0.37	-0.27	-0.22	-0.20	-0.26	-0.22	-0.27	-0.20	-0.27	-0.29	-0.24	-0.30	-0.33	-0.57	-0.35	-0.36	-0.44	-0.43	-0.41	-0.38
Mol	0.04	-0.08	0.02	0.06	0.08	0.03	0.05	0.01	0.07	0.02	-0.02	0.03	-0.03	-0.04	-0.27	-0.06	-0.06	-0.15	-0.16	-0.11	-0.08
Cam	-0.33	-0.47	-0.40	-0.34	-0.32	-0.37	-0.34	-0.39	-0.33	-0.39	-0.42	-0.35	-0.42	-0.44	-0.65	-0.47	-0.47	-0.54	-0.55	-0.51	-0.48
Pug	-0.05	-0.18	-0.09	-0.05	-0.03	-0.09	-0.05	-0.10	-0.04	-0.09	-0.13	-0.07	-0.14	-0.15	-0.35	-0.18	-0.16	-0.24	-0.25	-0.22	-0.19
Bas	-0.51	-0.62	-0.56	-0.51	-0.50	-0.53	-0.51	-0.55	-0.50	-0.55	-0.57	-0.53	-0.58	-0.61	-0.77	-0.63	-0.61	-0.68	-0.69	-0.66	-0.64
Cal	0.03	-0.10	-0.05	-0.00	0.03	-0.05	0.00	-0.07	0.01	-0.04	-0.08	0.02	-0.09	-0.08	-0.26	-0.13	-0.11	-0.17	-0.19	-0.14	-0.12
Sic	-0.58	-0.69	-0.64	-0.60	-0.58	-0.64	-0.59	-0.65	-0.59	-0.64	-0.66	-0.59	-0.67	-0.67	-0.80	-0.70	-0.69	-0.74	-0.75	-0.72	-0.70
Sard	0.09	-0.05	0.03	0.09	0.11	0.05	0.09	0.03	0.09	0.03	0.00	0.07	-0.00	-0.02	-0.26	-0.06	-0.05	-0.13	-0.13	-0.10	-0.06

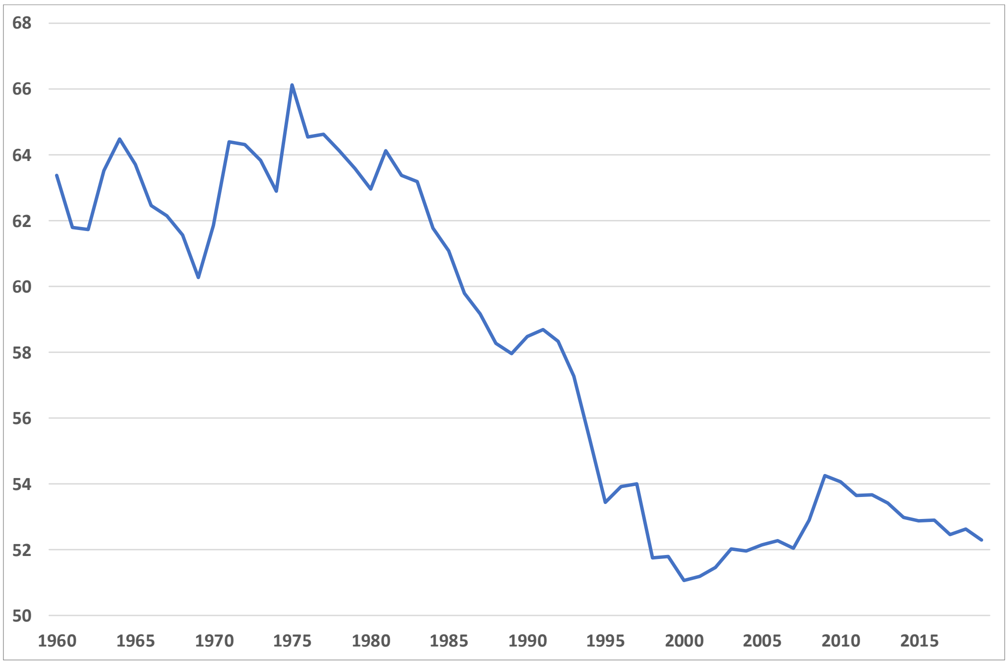

Figure 2: Adjusted wage share total economy: as percentage of GDP at current prices (Compensation per employee as percentage of GDP at market prices per person employed.). Source: EU - Ameco.

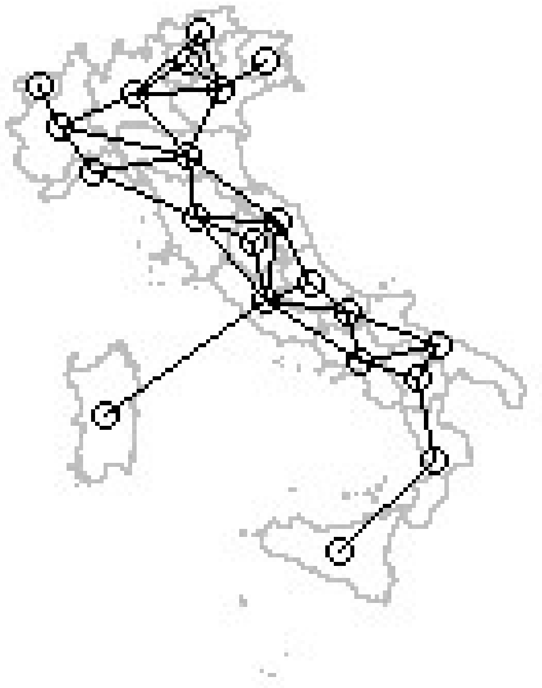

Figure 3: Connectivity Map

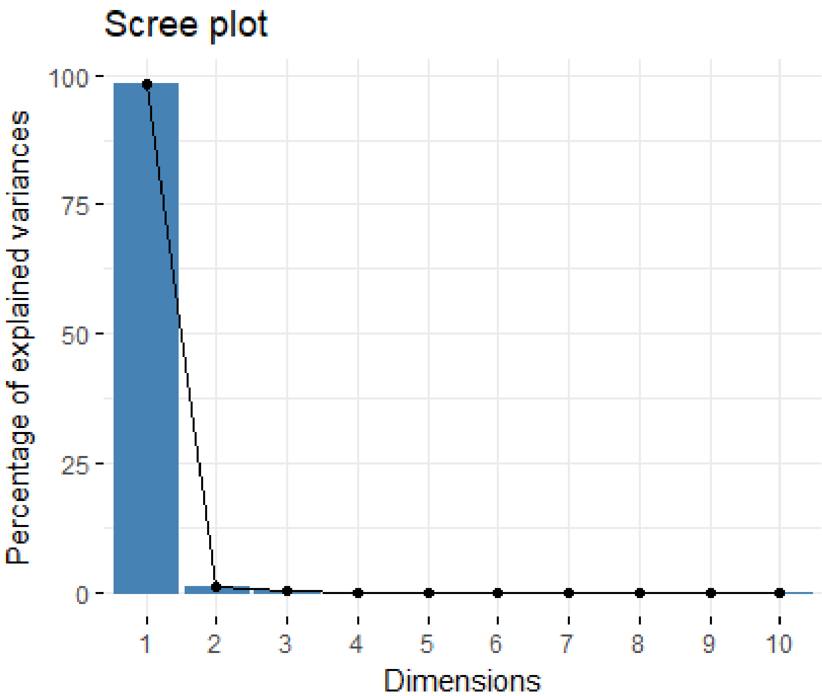

Figure 4: Scree Plot