An exploratory analysis on the determinants of regional resilience in Italy

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Abstract

This paper proposes a new and quite flexible econometric framework for measuring and explaining regional resilience. The overall effect of disaggregate responses to aggregate shocks is identified by combining linear error-correction models and non-linear smooth-transition autoregressive processes. Spatial interactions among neighbouring areas are also considered. The presence of asymmetries in resilience across Italian regions is investigated by looking at the evolution of employment over the period 1992(IV)-2012(IV). The following key results are obtained: regions within the same country differ in terms of both shock-absorption and post-recession patterns; the broad impact of a common shock shall take into account temporary and persistent effects; differences in recessions and recoveries among areas are motivated by some elements such as industrial structure, export propensity, financial constraints, human and civic capital. Some concluding suggestions introduce possible future areas of research in line with the more recent literature on this topic.

Keywords: regional resilience, nonlinearities, smooth transition regression, spatial effects, economic shocks.

JEL classification: R11, R12, C31, C32, O18.

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I. Introduction

During recessionary times the relation between negative shocks and economic growth usually regains its importance among academics and policymakers (recently, Calvo *et al.*, 2012; Cerra *et al.*, 2013). Whether or not output (employment or GDP) losses are reversed in a particular context is a crucial point like the comparison of the short and long term impacts associated to adverse events. And, these aspects assume a greater relevance if we consider particular areas or specific sectors of production.

Analysing the resilience of a country or a region affected by an economic crisis can be a promising way of assessing both the effects of negative shocks and the presence of jobless recoveries. Indeed, this perspective recently reintroduced in the economic debate (Martin, 2012) seems able to capture the overall path behind a given recessionary moment. On the one side, the so-called engineering resilience is associated to temporary equilibrium disturbances in line with the traditional real business cycle literature; on the other side, the concept of ecological resilience provide a useful framework for studying persistent out-of-equilibrium dynamics.

Empirical analyses in this area (among others, Fingleton *et al.*, 2012) have been mostly focused on the descriptive pattern of resilience, leaving only a marginal role to its determinants. This contribution aims to shed light on the latter aspect by proposing a possible alternative strategy for analysing the causes behind economic resilience. In particular, this paper presents a structural econometric approach which is capable to offer a quite general way for defining and estimating what determines economic resilience in its twin sense. The perspective hereafter adopted relies upon a two-step identification strategy.

In the first step, engineering resilience is modelled as the speed of adjustment to the long-run equilibrium obtained by estimating a linear Vector Error Correction Model (VECM) appropriately defined, while ecological resilience is identified as the degree of tolerance between regimes in the non-linear Smooth-Transition Autoregressive Model (STAR). Linear VECM results capture the ability of a given area to rebalance its (unique) long-run economic pattern and to which degree; the non-linear STAR specification introduces the possibility to discriminate across permanent multiple regimes and detect the switching point between them.

Both the speed of adjustment and the degree of tolerance resulting from the first step represent the dependent variables used in the second step in order to investigate the determinants of economic resilience. More specifically, cross-section techniques are

subsequently applied for providing explanations to the different resilient trajectories previously detected. In addition, the second step is enriched by introducing spatial interactions among neighbouring areas.

This strategy is applied to study the causes behind the divergent resilient employment dynamics showed by Italian regions in the last twenty years, as it has been documented in a companion working paper (Di Caro, 2013). Traditional explanations such as the industrial structure, financial constraints and human capital are considered together with less explored motives like export propensity and civic capital. As a result, this contribution also represents a possible alternative way for explaining growth differences across Italian regions.

Three are the main purposes of this paper. First, presenting a general strategy for identifying economic resilience and its determinants which can be also applied for cross-country comparisons. Second, contributing to the debate on the relation between growth and shocks by providing an alternative approach. Third, explaining the recent evolution experienced by Italian regions in terms of employment and providing some rationales behind the rooted Italian economic divide.

The remaining of the work is organized as follows. Section II presents some theoretical arguments which represent the basis for the subsequent empirical analysis. Section III identifies regional resilience in its twin sense. The determinants of resilience are illustrated in section IV. Section V summarizes and concludes.

II. Theoretical background

Economic resilience has been decomposed in 'engineering' resilience, the ability of a given area to bounce back after a negative shock, and 'ecological' resilience, multiple patterns of growth experienced by a system after a recession (Simmie and Martin, 2010; Martin, 2012). Both concepts can be applied to different geographical spaces (e.g. country, region, city) and different adverse events. Interestingly, economic resilience allows to combine two rooted traditions present in the economic literature studying recessions, namely the real business cycle approach and the multiple equilibria perspective.

On the one side, traditional real business cycle models are built upon the assumption of supply-driven Total Factor Productivity (TFP) shocks or neutral technology shocks (Justiniano *et al.*, 2010), and the natural rate hypothesis regarding unemployment. In this framework, recessions are temporary random fluctuations in the rate of technological

change, corresponding to periods of 'chronic laziness' (Mankiw, 1989). On the other side, permanent losses arising from adverse shocks are typically analysed by means of multiple equilibria models, nonlinear regimes and hysteresis in unemployment (Ball, 2009; Sinclair, 2009; Morley and Piger, 2012). Jobless recoveries, therefore, can perpetuate the long-term unemployment structure of a particular context: unemployment does not re-adjust in the long-run, being influenced by a negative hysteretic pattern (Blanchard and Summers, 1986).

Regional resilience offers the opportunity to look at the disaggregate responses to common shocks by correctly identifying the transient and permanent effects of aggregate disturbances on particular areas. And, this can become relevant in presence of geographical asymmetries during recessions and recoveries. As an illustrative example, if we consider economic output (employment or GDP) as a nonstationary process (Nelson and Plosser, 1982) [a], impulse responses functions for different recessionary events can be easily obtained by estimating a univariate autoregressive AR(p) model in growth rates[b].

In particular, the following model has been estimated for the Italian case:

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{J} \beta_j \Delta y_{i,t-j} + \sum_{s=0}^{S} \gamma_s D_{t-s} + \varepsilon_{it} \qquad (1)$$

where Δy_{it} is the percentage change in employment in the macro-region i (North-West, North-East, Centre, South[c]) at time t, D is a dummy variable denoting a given crisis, ε_{it} captures unobserved disturbances. Employment data range from 1977(I) to 2012(IV) and they have been preferred to GDP observations for two main reasons. First, the employment variable does not need to be deflated for each macro-region; second, quarterly GDP series are not available at macro-regional level for such a long time span.

The timing of the four main crises experienced in Italy in the last four decades derives from the identification of national-wide recessions, which have been obtained by investigating the Italian aggregate employment series. More precisely, the so-called exogenous approach (Harding and Pagan, 2002) has been applied, by combining the

[a] The nonstationarity of output (employment and GDP) has been previously tested by using the canonical methodologies. All test results related to this section are reported in the Appendix.

[b] Given the illustrative purpose of this econometric exercise, we limit our attention to the simplest version of the model presented in Cerra and Saxena (2008). For a more general version regarding this approach, see Cerra and Saxena (2008) and Cerra *et al.* (2013).

[c] These four aggregations have been classified by the Italian national institute of statistics (ISTAT) as follows: i) North-West: Piemonte, Valle d'Aosta, Liguria, Lombardia; ii) North-East: Trentino A.A., Veneto, Friuli V.G., Emilia Romagna; iii) Centre: Toscana, Umbria, Marche. Lazio; iv) South: Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna.

observation of output series with the official timing of Italian recessions provided by the Bank of Italy (Bassanetti *et al.*, 2010). As a result, four dummy variables have been introduced in the estimation: i) oil shock: 1978(IV) – 1979(II); ii) currency *Lira* crisis: 1992(IV) – 1994(I); iii) financial crisis: 2007(IV) – 2010(I); iv) debt and Euro crises: 2011(I) – 2012(IV).

Insert about here.
Figure 1. Impulse Responses: Italian recessions, 1977(I) – 2012(IV).

Figure 1 (a-d) illustrates the different behaviour showed by the four Italian macro-regions during every crisis in terms of responses to an one unit negative employment shock. Observing these figures, a couple of comments is worth noting. First, the dissimilar nature of each crisis seems to affect both the magnitude and the persistence of employment shocks. In the Italian case, for instance, the *Lira* crisis and the financial turmoil started in the second half of 2007 seem to have a longer impact (and magnitude) in terms of employment than the oil shock. The interpretation of the more recent twin crisis (Debt and Euro) shall be taken *cum grano salis*, given that it is not completely over.

Second, every crisis presents specific spatial patterns when disaggregating for macro-regions. In the early 1990s, for instance, the severe employment losses experienced in the South of Italy can be related to the joint effect of the *Lira* crisis and other events such as the abolition of the consolidated regional policy framework (i.e. *intervento straordinario*). Moreover, it is interesting to note that after the oil shock Italian macro-regions have progressively moved to more asynchronous dynamics.

Detecting and explaining regional resilience in its twin sense, therefore, can result helpful for two main reasons. It represents a promising way of studying the relations between shocks and unemployment disparities among regions within the same country, by complementing other approaches focusing on local labour market dynamics (Moretti, 2011; Greenaway-McGravy and Hood, 2013) and regional business cycles issues (Hamilton and Owyang, 2012). Moreover, it is a necessary preliminary step for assessing the case place-based fiscal and monetary policies: asymmetries in disaggregate reactions to shocks may require differentiated countercyclical mechanisms.

III. Detecting regional resilience

III.1 Methodology

A. Linear specification

For identifying engineering resilience we need to specify a model which is able to describe how regional employment responds to national-wide shocks within a given equilibrium framework. Since the influential contribution of Engle and Granger (1987), a common way of analyzing the joint behavior of macroeconomic time series has been linear cointegration. The cointegrating relationships have a structural interpretation: they represent the steady-state of long-run relations characterized by an error-correcting mechanism which is able to level off all shocks in order to allow the system to return to a balanced growth path (i.e. bounce-back or peak-reversion effect).

At this point, it shall be noted that the linearity requested by the Granger Representation Theorem implies at least three fundamental restrictions on the underlying economic behavior of the variables under observation (Escribano, 2004). First, it is assumed that the long-run equilibrium is unique. Second, the equilibrium correction mechanism (i.e. the adjustment toward the unique equilibrium) is symmetric. Third, the degree of adjustment is a constant proportion of the previous equilibrium error. In reality, these assumptions can result too restrictive for modeling macroeconomic series like employment and, then, the introduction of nonlinear aspects (as discussed in the next sub-section) can provide a better approximation of the phenomenon at hand.

For our purposes, we model engineering resilience as the speed of adjustment to the long-run equilibrium arising from the relation between regional and national employment. In particular, we are interested in showing how employment at regional level reacts to a one unit negative shock associated to national employment. Differences in the adjustment coefficients across regions represent potential signals of asymmetric engineering resilience: some regions correct faster their economic path after a country-wide disturbance than others.

Given that our main focus is to analyse the cointegrating relations between every regional employment series and the Italian counterpart, we estimate pairwise relationships connecting each of the 20 Italian regions to the national employment dynamic. Therefore, we adopt the Engle-Granger two-step cointegrating procedure for each bivariate vector resulting from a parsimonious econometric specification. A more detailed discussion of the

estimation procedure is presented in section III.2, together with the discussion of the main empirical results.

B. Non-Linear specification

Asymmetric behaviours over the business cycle and multiple regimes in (un)employment have been longer the focus of nonlinear time series analysis. The Markov-switching autoregressive model of Hamilton (1989), the self-exciting threshold autoregressive model of Beaudry and Koop (1993) and nonlinear error correction models (Escribano, 2004) are such examples of specifications aimed at capturing the multifaceted nature of recessions and recoveries. For a more detailed discussion, see van Dijk and Franses (1999), Skalin and Teräsvirta (2002), and Ferrara *et al.* (2013).

In order to study ecological resilience we need a flexible specification which is able to simultaneously describe the (possible) presence of multiple equilibria in regional employment and the impact of national-wide shocks on the evolution of regional economies. One promising way of addressing this question can be the application of the Smooth-Transition Autoregressive (STAR) model (Granger and Teräsvirta, 1993; van Dijk *et al.*, 2002). For a univariate time series y_t a general representation of the STAR model[d] is:

$$y_t = \phi_1' y_t^{(p)}\big(1 - G(s_t;\gamma,c)\big) + \phi_2' y_t^{(p)} G(s_t;\gamma,c) + \varepsilon_t \qquad (2)$$

where $y_t^{(p)} = (1, \tilde{y}_t^{(p)})'$, $\tilde{y}_t^{(p)} = (y_{t-1}, \dots, y_{t-p})'$, $\phi_i = (\phi_{i0}, \phi_{i1,} \dots, \phi_{ip})'$, $i = 1{,}2$ and ε_t is a white-noise error process with mean zero and variance σ^2.

The transition function $G(s_t;\gamma,c)$ is continuous and bounded between 0 and 1: in the existing literature, it has been generally represented as a logistic (LSTAR) or an exponential (ESTAR) function. In the following analysis, we adopt the logistic version:

$$G(s_t;\gamma,c) = \{1 + exp[-\gamma \textstyle\prod_{k=1}^{N}(s_t - c_k)]\}^{-1}, \qquad \gamma > 0 \qquad (3)$$

[d] The STAR model in (3) can be easily extended by adding exogenous variables as additional regressors (Teräsvirta, 1998), introducing multiple regime-switching points (van Dijk and Franses, 1999), considering autoregressive conditional heteroscedasticity (Lundbergh and Teräsvirta, 1998), and developing vector autoregressive versions (Camacho, 2002; Hubrich and Teräsvirta, 2013).

with γ denoting the speed of transition between regimes[e], N the total number of transition points, s_t the transition variable and c_k the threshold(s) value(s) indicating the level of the transition variable at which a transition point occurs.

The Logistic Smooth-Transition Autoregressive model (LSTAR) obtained by combining (2) and (3) represents, at any given point in time, the evolution of the variable y_t as a weighted average of two different linear autoregressive *AR(p)* models. The transition variable s_t determines the magnitude of the weights, while the parameter γ captures the speed at which these weights changes when s_t varies. As highlighted by van Dijk *et al.* (2002), the LSTAR model can be interpreted as a continuum of regimes depending on the different values of the transition function (between 0 and 1); or, alternatively, as a two-regime switching model where the transition from one regime ($G(s_t;\gamma,c) = 0$) to the other ($G(s_t;\gamma,c) = 1$) is smooth.

In this framework, a given output variable such as employment or GDP is in a particular regime according to the specific dynamic of the transition variable. In other words, variations in the transition variable are able to influence the regime-switching pattern showed by the autoregressive process under observation. In our case, the evolution of regional employment along a smooth transition path can be associated to variations of some national-wide variables which capture aggregate shocks. Changes in the national unemployment rate and unemployment growth at aggregate level are such plausible examples of forces governing the transition in employment across regions.

More specifically, the response of regional economies to national shocks is synthetized by the threshold parameter c, which can be interpreted as the degree of tolerance of a particular geographical area to a national-wide event[f]. Hence, differences between the transition variable s_t and the threshold c characterize the adjustment of a region after a recession/expansion in a multi-regime environment. For $s_t > c$ the process (smoothly) approaches the regime $G(s_t;\gamma,c) = 1$; while for $s_t < c$ the dynamic of the

[e] Three features of the parameter γ are worth noting: i) $\gamma > 0$ is an identifying restriction; ii) when $\gamma \to 0$ the model in (2) becomes linear; iii) when $\gamma \to \infty$ the logistic function approaches a Heaviside function, having the value 0 for $s_t < c$ and 1 for $s_t > c$.

[f] The LSTAR specification here presented can be also interpreted as the application of a spatial perspective to LSTAR models: indeed, the introduction of a national transition variable allows to investigate regional dynamics in more depth by linking aggregate shocks and disaggregate responses. A recent contribution (Kang *et al.*, 2012) has developed a similar line of argument to study the impact of aggregate oil price changes on the U.S. economy at state level. This approach, however, shall be distinguished from some new spatial versions of LSTAR models recently proposed (Pedé *et al.*, 2011; Lambert *et al.*, 2012).

variable y_t is moving towards the opposite regime $G(s_t; \gamma, c)$ = 0. Similar arguments can be extended to the case of more than one threshold point.

For our purposes, we model ecological resilience as the degree of tolerance showed by each region after estimating a LSTAR model for regional employment growth, where the transition variable is represented by changes in national unemployment. In presence of a common shock, differences in the threshold value across regions can be associated to diverse ways of reacting to an aggregate variation. An higher value of c will indicate a more (ecological) resilient region in the sense that a regime-switching in this area will occur for relevant values of the transition variable. In our case, then, a region with an high threshold level is able to bear larger national unemployment changes before moving towards a different employment state. Conversely, regions with low threshold values are triggered to alternative employment regimes when variations in the national transition variable are smaller.

III.2 Estimation results

A. Engineering resilience

The first-step econometric procedure is based upon quarterly data for Italian regional employment over the period 1992(IV) – 2012(IV), providing a quite reasonable number of observations (t=81) for the 20 Italian regions (NUTS II). The main data source is the Italian National Institute for Statistics (ISTAT). As previously discussed, engineering resilience across Italian regions is obtained by estimating a ECM relating each regional employment series to the national counterpart.

The stationarity of employment series has been verified using the traditional Augmented Dickey Fuller (ADF) test, while the optimal lag length has been chosen comparing different selection criteria: Akaike information criterion (AIC), Schwarz Bayesian information criterion (SBIC) and Likelihood Ratio (LR) test. Once recognized the presence of nonstationarity the cointegrating relationship between regional and national employment has been tested by means of the Engle-Granger residual-based cointegration test. Test results for every region are reported in the Appendix[9].

[9] All test results not reported in the Appendix are available from the author upon request.

Insert about here.
Table 1. Engineering resilience.

Given that all 20 regional employment series are linearly cointegrated with the national observations, we are able to obtain the speed of adjustment for each region responding to one unit negative aggregate shock by applying a parsimonious two-step Engle-Granger procedure. Table 1 shows these results for Italian regional employment series. As usual, the (symmetric) speed of adjustment captures the magnitude of correction showed by a particular area one period after a given aggregate shock.

Regional differences in the adjustment coefficients can be associated to different re-balancing patterns experienced by different areas after a national-wide adverse event. High levels of adjustment denote more (engineering) resilient regions, while less resilient areas are characterized by low adjustment coefficients. At this point, some aspects are worth commenting. In general, a sort of North-South divide seems to emerge from our results with more resilient regions mostly located in the North of Italy and less resilient ones in the South.

Nevertheless, a more accurate view allows to disentangle additional geographical features. Apart from the peculiar case of Trentino A.A., regions in the Centre of Italy such as Emilia Romagna, Toscana and Marche show the highest levels of adjustment across the *Peninsula*. Moreover, some Southern areas (Sardegna and Abruzzo) register the same degree of (engineering) resilience as some Northern counterparts. Calabria and Campania are characterized by the lowest degrees of engineering resilience in Italy.

B. Ecological resilience

For each Italian region the nonlinear LSTAR specification is estimated by applying the modelling approach proposed by Teräsvirta (1994): a) specifying a linear $AR(p)$ model for the dependent variable under analysis; b) testing the null hypothesis of linearity against the alternative of STAR; c) if linearity is rejected, defining the appropriate transition function; d) estimating the model by conditional maximum likelihood (or nonlinear least squares); e) conducting post estimation robustness checks.

Our dependent variable is quarterly regional employment growth from 1992(IV) to 2012(IV) for the 20 Italian regions. The lag length of each process has been selected by applying traditional methods such as AIC/SBIC in order to rule out serial correlation. The transition variable determining the value of the logistic transition function is represented by

the Italian unemployment growth rate for the period 1992(IV) – 2012(IV). The choice between one (LSTR1) or two (LSTR2) threshold values has been operated by following the sequential procedure indicated by Teräsvirta (2004). Test results are reported in the Appendix.

The presence of nonlinearity has been rejected for four regions, namely Valle d'Aosta, Trentino A.A., Friuli V.G. and Basilicata[h]. Regional employment for four regions (Lombardia, Emilia Romagna, Toscana and Abruzzo) has been modeled by applying the LSTR2 specification with two threshold values. Nonlinearity tests have been set up with a maximum lag length of the transition variable of two years ($d = 8$). For our purposes, we limit our attention to the degree of tolerance (parameter c) registered by each Italian region.

At a first glance, we can observe differences in the delay parameter d across regions, denoting different time responses to the transition variable. In presence of an high delay as in the case of Piemonte and Calabria (t – 8), the effect of the transition variable (i.e. national unemployment) on the changing pattern of regional employment is completed about two years later the initial aggregate shock. On the contrary, shorter time delays like those showed by Abruzzo (t) and Puglia (t-1) characterize a (quasi) immediate switching process: regional employment states are triggered few periods after the national-wide event.

Table 2 illustrates STAR results for Italian regions. In case of two threshold values (LSTR2) it has been reported the higher degree of tolerance ($c_2 > c_1$). Indeed, when two threshold points are present, namely in the LSTR2 specification, transition occurs at two different points. For our purposes, the higher one assumes a critical relevance. A more detailed description of estimation results is presented in the Appendix.

Insert about here.
Table 2. Ecological resilience.

From the nonlinear perspective here adopted three aspects are worth pointing out. First, Italian regions seem to present different degree of tolerance (i.e. ecological resilience) to a common shock in national unemployment. Some regions (smoothly) approaches a diverse employment state for relevant positive changes of the transition variable: for

[h] More precisely, for these regions we are not able to reject linearity in favor of a nonlinear STAR specification. This can be due to the presence of high serial correlation in these series (i.e. which significantly reduces the power of the test here applied) or to the necessity of finding out alternative nonlinear specifications. From an economic point of view, this result can be ascribed to the particular structure of these regions, having limited industries and mostly based upon seasonal activities such as tourism (especially Valle d'Aosta and Trentino A.A).

example, Toscana completely switches to a worse scenario when national unemployment rise by more than 23%, say from about 8.5% to 10.4%. Conversely, in some areas like Campania the transition occurs at lower values: this specific region (negatively) changes its dynamic even when national unemployment decreases by less than about 15%.

Second, ecological resilience seems to confirm the spatial unevenness of recessions and recoveries across Italian regions. More (ecological) resilient areas are in the Centre of Italy (Emilia Romagna, Toscana, Marche), whereas less resilient areas are in the South (Molise, Campania and Calabria). Once again, however, a more mixed picture emerges, with high/low resilient spaces spread across the *Peninsula*.

Third, some results regarding engineering resilience are also confirmed in the ecological case. Liguria, for instance, continues to register a low level of resilience, though this region is in the North of Italy, while Puglia and perhaps Sardegna show more resilient features than other Southern contexts. This evidence can partially explain why during the current recession, over the period 2008(II) – 2013(I), the variation in the unemployment rate has been somewhat deeper in Liguria (+6.53%) than in Puglia (+5.57%).

Insert about here.
Figure 2. Selected smooth transition functions.

Figure 2 shows the smooth transition function $G(s_t;\gamma,c)$ for selected Italian regions. Apart from different time delays among these geographical areas, it is interesting to note the diverse threshold values at which employment regime-switching occurs. The transition in Piemonte and Puglia starts when national unemployment changes more than about 4%. Moreover, Piemonte registers a more pronounced speed of transition than Puglia: once the transition variable reaches its switching point the passage between regimes is faster. Umbria and partially Sardegna are examples of negative thresholds, with the former denoting a lower degree of tolerance to national-wide shocks than the latter.

IV. Explaining regional resilience

IV.1 Data source and description

In this section, the determinants of regional resilience in its twin sense are investigated by means of some explanatory variables with the adoption of two different time definitions: the initial year of the time period under observation following the well-

known method *à la* Barro and the average time horizon over the years 1992 – 2012. The former methodology derives from a convergence-based approach where the evolution of a given variable can be explained by the initial conditions of some determinants. In a complementary way, the latter one allows us to consider the time variation of each explanatory variable.

One plausible explanation behind the economic resilience of a particular area can be based upon the characterizing aspects of its industrial structure: different productive contexts can show asymmetric recovery patterns. As recently indicated by Dani Rodrik (2013), for instance, most of manufacturing industries produce tradable goods which can be integrated into global production networks, facilitating technology transfer and innovation updating. Moreover, the presence of particular sectors is naturally associated to a higher sensitivity to industry-specific shocks and sector-tailored efficient mechanisms.

In the following analysis, we focus on three sectors at regional level, namely manufacturing, non-public services and public activities. For every sector two variables have been defined for each time horizon previously discussed: percentage of regional sector-specific added value and Krugman absolute specialization index. A more detailed description of all the variables used in this section is contained in the Appendix.

In addition, the economic evolution of a given region after a recession can be influenced by trade and exports. Since the seminal contribution of Frankel and Romer (1999), the importance of export-oriented activities has been related to economic growth through several channels: specialization arising from comparative advantages, exchange of ideas and technologies, product innovation and increasing returns from larger markets. Therefore, regions may become what they export and they are able to recover in the long run by focussing on specific tradable goods.

The importance of trade for economic resilience is measured by using an index based upon the revealed comparative advantage approach as theorized by Hausmann and Rodrik (2003). This index is obtained as follows. Firstly, it is constructed an index called *PRODY* which is the export-weighted average of the income/productivity level of a region exporting a given product. Let regions be denoted by i and goods by j, per-capita GDP of region i be Y_i, x_{ij} the export share of product j in region i and X_i the total regional export basket. The productivity level associated with product j, $PRODY_j$ equals to:

$$PRODY_j \equiv \sum_i \frac{\left(\frac{x_{ij}}{X_i}\right)}{\sum_i \left(\frac{x_{ij}}{X_i}\right)} Y_i$$

where regional per-capita GDP is weighted by the revealed comparative advantage of each region in good j.

Subsequently, for each region it is obtained an index called *EXPY* which ranks traded goods in terms of their implied productivity: this can be interpreted as an inverse of the well-known Balassa revealed index. The *EXPY* index for region i export basket is

$$EXPY_i \equiv \sum_j \left(\frac{x_{ij}}{X_i}\right) PRODY_j$$

with each sector-specific *PRODY* weighted by the value share of the product in the region's total exports. Regions with an high level of *EXPY* denote areas specialized in high productive activities (i.e. 'rich-country products').

For the period 1992 – 2012, we collect detailed observations for 38 product categories exported by the 20 Italian regions to the rest of the world. From this dataset, two measures are constructed: *EXPY*, considering all the product categories; *MADEITALY*, limiting the observation to 17 product categories which represent the traditional 'Made in Italy' activities such as machineries, mechanicals, design and creative industries.

Human capital *lato sensu* is another possible candidate to explain differences in resilience across regions. As pointed out in a recent contribution (Gennaioli *et al.*, 2013), the multiple effects of education on regional development can be articulated in three distinct areas: education of workers, education of entrepreneurs and externalities. Well educated workers contribute to increase productivity, to rise the aggregate level of skills in the economy and to bolster the generation of new ideas. Skilled entrepreneurs act as innovative agents by introducing, developing and valorising new ways of production and organisation. And, human capital returns are not only limited to private benefits but they overflow in pecuniary and non-pecuniary externalities.

Concerning the education of workers we construct a measure (*HUMCAP*) capturing the average years of educational attainment of the population in a given region.

More specifically, as in Barro and Lee (2012) this variable is obtained by weighting the educational attainment (primary, lower secondary, upper secondary, tertiary) achieved by a fraction of the total population (> 15 years) for the corresponding duration in years of the specific educational level. For the 20 Italian regions Census data are available covering the period 1991 – 2011[i]. The variable capturing entrepreneurial human capital (*HUMCAPENTR*) has been obtained as in Gennaioli *et al.* (2013), measuring the percentage of bureaucrats with a college degree. These data are referred to the Census year 2001 and they derive from the International IPUMS database.

Asymmetric regional evolutions can be explained through the presence of different stocks of civic capital: a set of shared beliefs and values that help a group to overcome free riding issues in the pursuit of socially valuable activities (Guiso *et al.*, 2010). Public trust, mutual cooperation and sense of community can reduce transaction costs, stimulate the accumulation of physical and human capital, improve government performance and the quality of public administration. Moreover, high civic contexts show less coordination failures given that civic capital helps to limiting moral hazard and adverse selection.

To measure civic capital at regional level we use the electoral participation to referenda registered in the Italian regions over the period under consideration (*CIVIC*)[j]. This proxy has been part of the set of indicators used by Robert Putnam and his colleagues (1993) for analyzing the civicness of Italian regions and it can be understood as an indirect manifestation of civic attitude due to the general issues covered by referenda. In addition, we use the number of blood donations divided for the population (> 15 years) at regional level as a complementary measure.

Lastly, we investigate the effect of financial constraints on regional resilience. It is well-known that high interest rates and tight financial markets can act as a barrier to investment in high-return activities, reducing the creation of new firms and amplifying the cyclical effects of economic crisis during negative times. And, these aspects can become even more relevant in presence of a spatially-anchored credit system as in the Italian case,

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[i] Census data are available for the years 1991, 2001 and 2004 – 2011. Missing observations (1991 – 2001; 2001 – 2004) are filled through linear interpolation, given the limited time variation of this variable. However, other measures of human capital (e.g. the measure used by Gennaioli *et al.*, 2013) have been compared in the empirical part resulting in similar conclusions.

[j] Since 1993 there have been 8 national referenda in Italy regarding different arguments such as the abolition of public financing to political parties, privatizations and the modification of the electoral system. The average participation to the referendum in 1993 represents the measure for the initial year, while for the overall period it has been calculated the average participation to all referenda.

where there are still today strong regional differences among credit markets (Giannola and Lopes, 2012).

As a proxy for financial constraints, we adopt the average interest rate paid by obtaining a specific financing operation generally used by firms (i.e. *operazioni a revoca*). The choice of this variable can be motivated by two main reasons. First, data availability covering the time horizon of interest. Second, this particular measure does not include the interest rate attached to non-performing credits (higher during recession periods), overcoming some endogeneity problems. The data source for this variable is the Bank of Italy.

IV.2 Estimation results

A. Engineering resilience

As a preliminary step, simple (Pearson) correlation indexes between engineering resilience and the set of explanatory variables previously discussed is illustrated in table 3. In general, engineering resilience is positively correlated with the presence of manufacturing industries, export propensity, human and civic capital. Conversely, non-public services, public activities and financial constraints seem to hamper the recovery ability of regions after a generic shock.

Insert about here.
Table 3. Correlation between engineering resilience and explanatory variables.

Using engineering resilience as dependent variable some cross-regional regressions are hereafter presented in order to investigate the determinants behind the asymmetric behavior showed by the 20 Italian regions. Due to the short number of observations in our sample, it has been preferred to conduct various estimations by grouping the set of explanatory variables. Estimation results are illustrated in tables 4 (A – D).

Insert about here.
Table 4. Cross-regional regressions.

In line with most of the business cycle literature, the ability of a given region to bounce-back after a recession seems positively related to its level of manufacturing structure, which can stimulate higher investments, capital accumulation, productive

linkages and a more competitive environment. On the contrary, a relevant presence of services and public activities can have a negative impact on the resilience of a given region: most of employment opportunities in non-public services are traditionally connected to the dynamic of production in a cyclical way, while public employment programs are typically less flexible than private ones[k].

Interestingly, when we consider Krugman specialization indexes (i.e. the degree of sector-specific similarity between each region and the national aggregate) the situation appears more puzzled. Regarding the time period as initial year, it can be noted the negative sign of the Krugman manufacturing index and the positive sign of the indexes calculated for services and public activities. One possible interpretation of these results can be that regions having more similar manufacturing structures to the Italian one (i.e. with a low Krugman index) are able to react faster after a national-wide shock. The opposite is true when taking into account the other two sectors.

Alternatively, differences in the specialization pattern between regions can produce asymmetric responses to sector-specific shocks. For instance, if a region relies upon non-public services more than the Italian aggregate (i.e. with an high Krugman index), it will be probably affected deeper by a national recession originating from the service sector and, consequently, its recovery will result more difficult. However, these observations shall be taken *cum grano salis* given that when considering the other time period (average 1992 – 2012) our estimation results show low significance levels.

Table C relates engineering resilience to additional explanatory variables. A positive value of both *EXPY* and *MADEITALY* as previously defined seems to encourage the recovery phase experienced by a given region after a shock. Since the early Keynesian tradition the regional export basket has been relevant for explaining growth differences and economic evolutions at territorial level (Rowthorn, 2010). And, this variable plays a more important role if weighted for productivity levels as we did. It is not a case, then, if high resilient regions like Emilia Romagna, Toscana, Veneto and Marche show the highest levels of *MADEITALY*.

The positive sign of the variable *CIVIC* measured as the participation to referenda, also confirmed when using *BLOOD* thereof, denotes the importance of cooperation and

[k] It shall be noted, moreover, the peculiar situation of the Italian case with respect to both non-public services and public employment. The former have been historically organized on a low-scale basis, with small and medium enterprises representing the majority of firms. Since the early 1990s, public employment turnover has been consistently reduced through the so-called '*blocco delle assunzioni*' generating a decreasing trend in public employment opportunities.

mutual confidence for the evolution of a particular economic context. On the contrary, the presence of financial constraints captured by an high interest rate hampers the resilience of a region: the tighter the credit market is, the slower the recovery will be. In 1992, for instance, the interest rate paid for the same financial operation was 21.04% in Basilicata and 17.6% in Piemonte.

Finally, table 4D relates engineering resilience to human capital in its twin sense: education of workers and education of entrepreneurs. Regions having a more educated workforce perform better in terms of resilience than regions reporting a low level of human capital. The negative sign associated to entrepreneurial human capital is probably due to the particular measure here adopted (the percentage of bureaucrats with a college degree) biased towards public employment.

B. Ecological resilience

As described in section III.2.B, after the first-step we have excluded four regions resulting in 16 available observations for conducting second-step analysis for ecological resilience. Although the smaller sample probably influences the significance of estimation results, the same investigation as before is conducted for comparative purposes. Table 5 reports correlation indexes between ecological resilience and the set of explanatory variables.

Insert about here.
Table 5. Correlation between ecological resilience and explanatory variables.

In general, correlation indexes seem to confirm what it has been founded in the previous case. Ecological resilience at regional level is positively affected by the manufacturing structure, the productivity-weighted level of exports, specific categories of exported goods (i.e. *MADEITALY*) and the overall endowment of human capital. Favorable effects in terms of resilience are also associated to the presence of civic capital. On the contrary, financial constraints appear to hinder ecological resilience as well as an industrial structure which relies upon non-public services and public activities.

Insert about here.
Table 6. Cross-regional regressions.

Tables 6 (A – D) report cross-section estimation results grouped for disentangling the determinants of ecological resilience. Most of the comments previously proposed for explaining engineering resilience are still valid. Regions are more resistant to aggregate shocks, showing higher resilience before moving to another equilibrium, when they have a relevant concentration of manufacturing, a low level of public activities and less financial constraints.

Now, the Krugman specialization indexes show statistical significance only when taking into account the time period defined as initial year. Perhaps, this can be due to the progressive reduction of regional specialization patterns (on average) with respect to the national aggregate registered over the period 1992 - 2012. Indeed, differences in Krugman indexes at the beginning of the period (i.e. denoting a more articulated regional structure relative to the Italian aggregate) have gradually decreased.

In this case, the impact of civic capital on resilience has been captured by using the variable *BLOOD*, given that when using the variable *CIVIC* estimation results are not statistical significant. This element can be explained by noting that the inter-regional differential of *BLOOD* is higher than that of *CIVIC*, and the same difference can be observed when comparing ecological with engineering resilience. When considering human capital the same comments as in the engineering resilience case can be applied.

IV.3 Spatial Estimation

A possible interesting question when looking at regional resilience can be the identification of potential spatial patterns: interactions among neighboring areas matter for the recovery of a given territory. Traditional spillovers, productive interdependencies, commuting of workers and joint initiatives are some of the possible channels through which regional resilience can trickle-down from one place to another. And, a correct identification of the spatial effects at work results fundamental in order to better understanding the phenomenon at hand.

Observed and unobserved components can drive spatial relations. A simple way of specifying spatial effects is the traditional Cliff–Ord representation or spatial autoregressive model with a spatial autoregressive disturbance (SARAR). Specifically, the presence of cross-sectional interdependences may derive from interactions regarding the dependent variable (γ), interdependencies in the error terms (ρ), or both. A general SARAR representation is:

$$\boldsymbol{y} = \gamma \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\beta + \boldsymbol{u} \tag{4}$$

$$\boldsymbol{u} = \rho \boldsymbol{M}\boldsymbol{u} + \boldsymbol{\varepsilon} \tag{5}$$

where $\boldsymbol{y}$ is the $N\,x\,1$ vector of cross-sectional observations on the dependent variable, $\boldsymbol{X}$ is the $N\,x\,k$ matrix of observations on the explanatory variables, $\boldsymbol{W}$ and $\boldsymbol{M}$ are $N\,x\,N$ spatial-weighting matrices capturing the distance between neighborhoods[I], $\boldsymbol{u}$ are spatially correlated residuals, $\boldsymbol{\varepsilon}$ are *i.i.d.* disturbances, and γ, β, ρ parameters to be estimated.

Before starting spatial estimations, we need to define the spatial weight matrix $\boldsymbol{W}(n\ x\ n)$, with ω_{ji} ($j \neq i$) denoting an individual element of it, and test for the presence of spatial effects (i.e. conducting the canonical Explanatory Spatial Data Analysis). Our $\boldsymbol{W}$ represents the inverse of the geographical distance between centroids (i.e. regional capital) of the k-nearest neighbours (k = 10, 15, 20). Estimates and tests hereafter reported have been obtained using the value k = 10 and applying a row-standardization of the spatial matrix. The maximum value of 10 neighbours seems reasonable for capturing geographical interactions across Italian regions.

Regarding the presence of spatial effects, the Moran's I global statistics is equal to 0.410 (E(I) = -0.053) and 0.127 (E(I) = -0.067) for engineering and ecological resilience respectively. In both cases, test results are significant at 1% level. Hence, we can expect a possible similar relation between resilience of contiguous regions. On the one side, the process of adjustment of a given place after a shock can be influenced by the adjustment occurring in its neighbours. On the other side, regime changes in employment occurring in a particular area after a common shock can be linked to the same pattern experienced in neighbouring places.

Insert about here.
Figure 4. Moran's scatterplot.

Insert about here.
Table 7. Moran's local index.

While global spatial measures such as the Moran's I global statistics allows to identify the overall presence of spatial autocorrelation in the sample, we need to employ

[I] In the following analysis it is assumed, without loss of generality, a unique spatial weight matrix, namely $\boldsymbol{W} = \boldsymbol{M}$.

local statistics in order to disentangle possible spatial clusters across units. These are showed in Figure 4 and Table 7, which report the Moran's I local scatterplot and index for engineering and ecological resilience respectively. As a consequence, it is worth noting that spatial effects are more spread when considering engineering resilience. From figure 4 (left panel), for instance, it can be observed the presence of two main clusters in Italy: regions showing high levels of resilience tend to be closed (upper right quadrant) and the same happens for regions having low resilience (lower left quadrant). Moreover, this pattern is confirmed when comparing the value of Moran's I local index. Once again, spatial interactions seem to be higher for engineering resilience.

Insert about here.
Table 8. Spatial ML estimation engineering resilience.

From the previous discussion, it results more appropriate to investigate spatial effects by looking at engineering resilience. Tables 8 (A – D) report spatial estimation results for engineering resilience obtained by applying Maximum Likelihood estimator. Starting from a general-to-specific approach, it has been conclusively selected the spatial autoregressive (SAR) model (i.e. $\rho = 0$) on the basis of the Likelihood Ratio test. Almost all cross-sectional regressions show a positive and significant spatial dependence across Italian regions. Regional engineering resilience, then, seems to be driven by interregional dynamics and the evolution of contiguous contexts.

Different channels can justify the presence of regional co-movement in terms of resilience. Cross-border investments, commuting flows and complementary product specialization in adjacent regions are some of these elements. For instance, it is well-known the importance of inter-regional links within the boundaries of historical districts like those present between Marche and Emilia-Romagna in the Centre-North or between Campania and Lazio in the Centre-South. Therefore, engineering resilience in one region seems to be influenced by the way a contiguous place reacts to aggregate shocks. These aspects, however, need to be further clarified by investigating the reasons behind spatial effects of shocks which is outside the boundaries of the present paper.

V. Conclusion

Paraphrasing Romer and Romer (1994), this paper has been developed around the twin research question: where and why recession ends (or not)? Differences in regional resilience have been used as a starting point in order to analyse the evolution of regional employment after a given aggregate shock. Temporary and persistent effects have been distinguished by applying two complementary econometric procedures, namely linear and nonlinear. The following key results are obtained for the Italian case: regions differ in terms of both shock-absorption and post-recession patterns; disaggregate responses vary when taking into account temporary and persistent effects of crises; differences in recessions and recoveries among areas are motivated by some elements such as industrial structure, export propensity, financial constraints, human and civic capital.

Three main insights and two notes for future research can be derived from the previous pages. First, this contribution explicitly introduces a new empirical approach for discriminating between engineering and ecological resilience, participating to the recent debate on detecting and measuring resilience (Fingleton and Doran, 2013). Second, the determinants of regional resilience asymmetries have been investigated and clearly pointed out: in this sense, the present analysis integrates the existing literature by providing a formal view for identifying the causes behind a diverse resilient path. Third, if the geography of crises and recoveries matters within a country, then, the claim for place-based (Barca *et al.*, 2012) countercyclical policies receives further justifications.

In line with the more recent literature on this topic (Angulo *et al.*, 2013; Fingleton and Palombi, 2013), the empirical approach heretofore suggested can be completed by focusing on possible forecasting speculations and counterfactual experiments. In addition, a natural further step of investigation is the analysis of the place-specific effects related to fiscal and monetary policies. These and other questions are left for future research.

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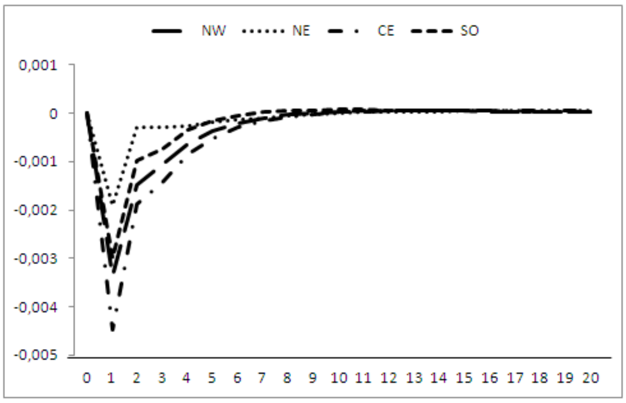
Tables and Figures

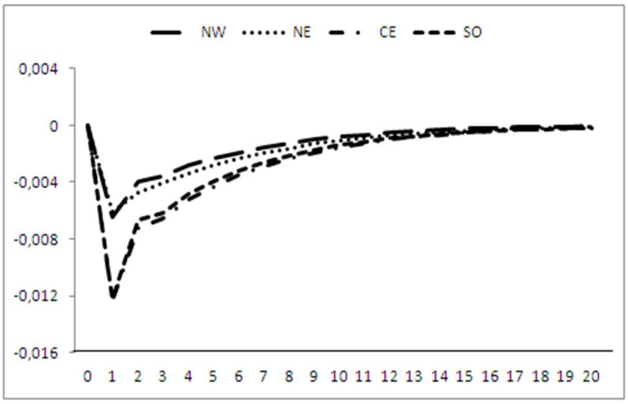
Figures

Figure 1. Impulse Responses: Italian recessions, 1977(I) – 2012(IV)

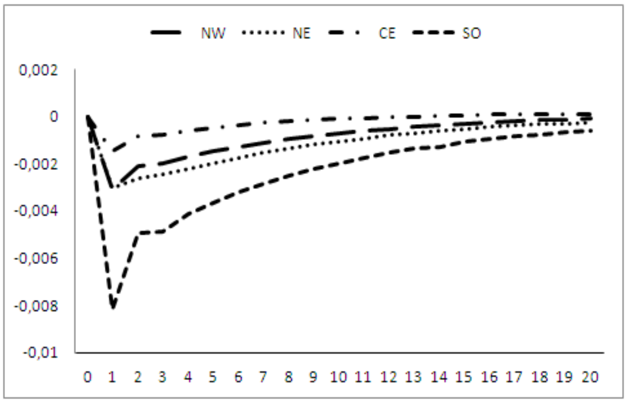
(a) Oil Shock



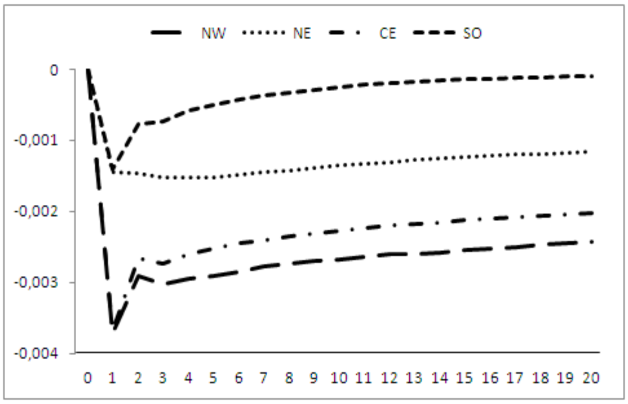
(b) Currency ‘Lira’ Crisis



(c) Financial Crisis



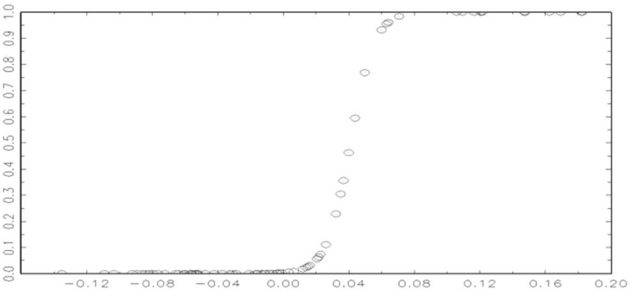
(d) Debt and Euro Crises



Note: Figure 1 (a-d) reports impulse responses (y axis) over periods 1-20 (x axis), for four Italian macro areas (North-West, North-East, Centre and South), obtained by estimating the model in (1).

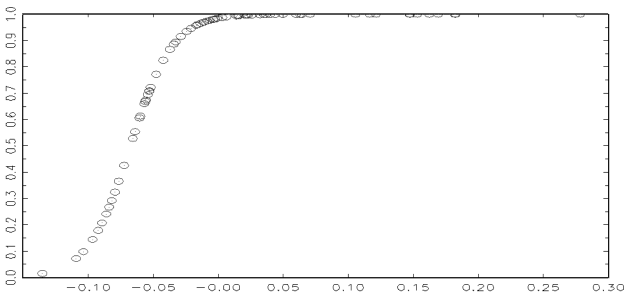
Figure 2. Selected smooth transition functions

Pie



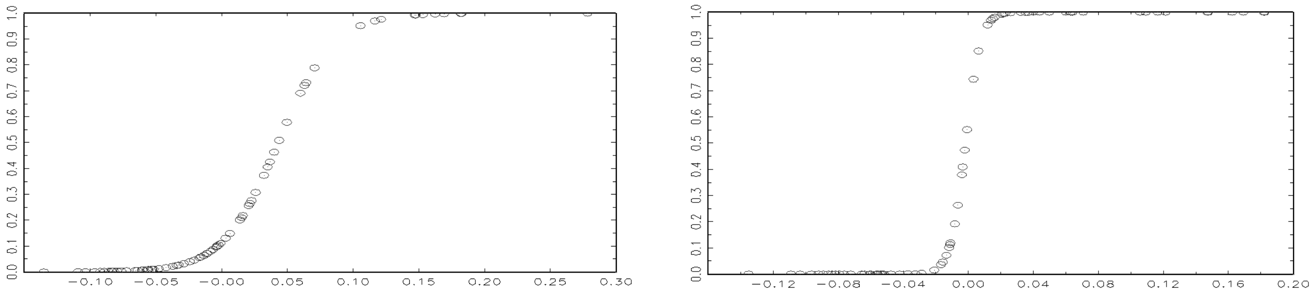
ΔUnemp Italy (t-8)

Umb



ΔUnemp Italy (t-2)

Pug *Sar*

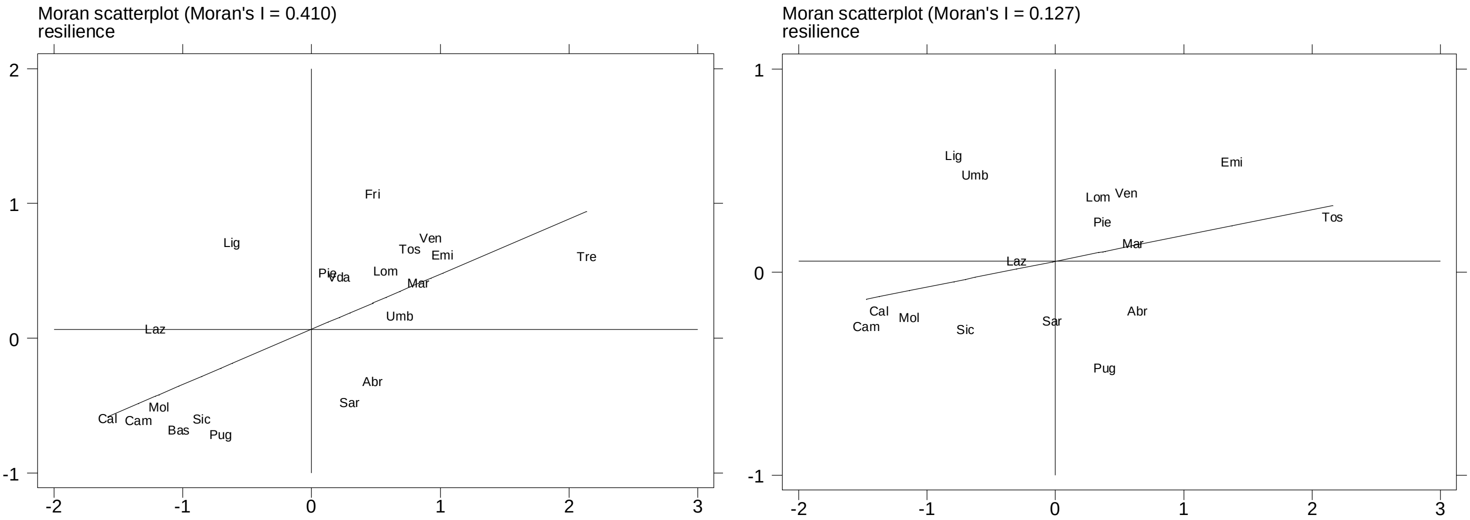


ΔUnemp Italy (t-1) ΔUnemp Italy (t-6)

Note: Figure 2 reports the smooth transition function (y axis) in relation to the variation of the transition variable (x axis) for selected Italian regions, obtained by estimating LSTAR models.

Figure 4. Moran's scatterplot

Engineering resilience *Ecological resilience*



Note: Figure 4 plots the spatial dependent variable WY (y axis) against the dependent variable Y (x axis), with Y denoting resilience.

Table 1. Engineering Resilience

Region	speed of adjustment
Piemonte	0.43316
Valle d'Aosta	0.42056
Lombardia	0.48438
Liguria	0.31509
Veneto	0.53381
Trentino A.A.	0.70490
Friuli V.G.	0.46964
Emilia Romagna	0.54686
Toscana	0.51084
Umbria	0.49964
Marche	0.52044
Lazio	0.23058
Abruzzo	0.47003
Molise	0.23460
Campania	0.21208
Puglia	0.30242
Basilicata	0.25637
Calabria	0.17832
Sicilia	0.28147
Sardegna	0.44443

Table 2. Ecological Resilience

Region	Degree of tolerance
Piemonte	0.04098
Lombardia	0.03758
Liguria	-0.08514
Veneto	0.06131
Emilia Romagna	0.15074
Toscana	0.23614
Umbria	-0.06746
Marche	0.06669
Lazio	-0.03244
Abruzzo	0.07065
Molise	-0.12344
Campania	-0.15964

Puglia	0.04304
Calabria	-0.14902
Sicilia	-0.07582
Sardegna	-0.00171

Table 3 – Correlation between engineering resilience and explanatory variables

Variable	Correlation Index	
Time period:	initial year	average period
MANUF_STRUC	0.6624	0.6306
SER_STRUC	-0.5227	-0.4792
PA_STRUC	-0.7707	-0.7353
KRUG_MANUF	-0.6173	0.0237
KRUG_SER	0.3393	-0.3562
KRUG_PA	-0.2185	-0.1639
EXPY	0.3361	0.3818
MADEITALY	0.1582	0.1471
FINANC	-0.4769	-0.6583
CIVIC	0.6425	0.7379
HUMCAP	0.4909	0.2145
HUMCAP_ENTR	-0.7130	

Note: initial year (1992), average period (1992 – 2012), observations for *HUMCAP_ENTR* are available for the only Census year 2001.

Table 4 (A-D). Cross-regional regressions

(A)

Dependent Variable: Engineering Resilience				
Time period:	Initial Year		Average 1992-2012	
	(1)	(2)	(1)	(2)
MANUF_STRUC	1.1615***	-	1.3534***	-
	(0.3057)		(0.2395)	
SER_STRUC	-2.3200**	-2.5144***	-1.4299**	-0.9854**
	(0.8603)	(0.6070)	(0.4838)	(0.5038)
PA_STRUC		-1.8410***		-1.6767***
		(0.2017)		(0.2949)
Constant	0.6440***	1.3172***	0.5056***	1.0244***
	(0.2035)	(0.1394)	(0.1459)	(0.1479)
Observations	20	20	20	20
R^2	0.61	0.80	0.59	0.63
Prob > *F*	0.0000	0.0000	0.0003	0.0001
Root MSE	0.0939	0.0676	0.0954	0.0913

(B)

Dependent Variable: Engineering Resilience				
Time period:	Initial Year		Average 1992-2012	
	(1)	(2)	(1)	(2)
KRUG_MANUF	-2.3819***	-2.8833***	0.6670	1.0387
	(0.3866)	(0.6532)	(1.0343)	(1.2905)
KRUG_SER	2.4343*	3.4539**	-1.8174**	-1.6949**
	(1.5364)	(1.5108)	(0.7438)	(0.7776)
KRUG_PA		1.3574		-0.8566
		(0.9898)		(1.3646)
Constant	0.5156***	0.4660***	0.4213***	0.4374***
	(0.0450)	(0.0392)	(0.0667)	(0.0707)
Observations	20	20	20	20
R^2	0.45	0.51	0.15	0.17
Prob > *F*	0.0000	0.0000	0.0772	0.1059
Root MSE	0.1105	0.1084	0.1382	0.1407

Note: Robust standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.

(C)

Dependent Variable: Engineering Resilience								
Time period:	Initial year				Average 1992-2012			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
EXPY	0.0820* (0.0459)	0.0808* (0.0416)	-	-	0.0145* (0.0094)	0.0175* (0.0114)	-	-
CIVIC	0.0143*** (0.0037)	0.0129*** (0.0030)	0.0112*** (0.0031)	0.0097*** (0.0027)	0.0164*** (0.0021)	0.0124* (0.0021)	0.0159*** (0.0017)	0.0125** (0.0060)
FINANC		-0.0253* (0.0173)		-0.0240* (0.0179)		-0.0291* (0.0188)		-0.0287* (0.0173)
MADEITALY			0.0156* (0.0112)	0.0147* (0.0103)			0.0158* (0.0114)	0.0146* (0.0105)
Constant	0.4253 (0.4157)	0.5995 (1.0005)	-0.3012* (0.1677)	-0.2526 (0.3965)	-0.1614 (0.2516)	-0.2940 (0.6603)	-0.2190 (0.0669)	0.2012 (0.7669)
Observations	20	20	20	20	20	20	20	20
R^2	0.45	0.53	0.46	0.49	0.56	0.58	0.57	0.59
Prob > *F*	0.0011	0.0014	0.0041	0.0065	0.0000	0.0000	0.0000	0.0000
Root MSE	0.1072	0.1079	0.1104	0.1115	0.1007	0.1011	0.0918	0.1002

Note: Robust standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.

(D)

Dependent Variable: Engineering Resilience				
Time period:	Initial year		Average 1992-2012	
	(1)	(2)	(1)	(2)
HUMCAP	0.1368* (0.0782)	0.0759* (0.0467)	0.0881* (0.0572)	0.0693* (0.0465)
HUMCAP_ENTR		-22.90*** (5.469)		-26.08*** (5.223)
Constant	-0.6635 (0.5949)	0.1670 (0.4051)	-0.3919 (0.8329)	0.1833 (0.5062)
Observations	20	20	20	20
R^2	0.25	0.57	0.27	0.54
Prob > *F*	0.0097	0.0004	0.0078	0.0005
Root MSE	0.0978	0.0972	0.1202	0.1001

Note: Robust standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.

Table 5 – Correlation between ecological resilience and explanatory variables

Variable	Correlation Index	
Time period:	initial year	average period
MANUF_STRUC	0.6590	0.5650
SER_STRUC	-0.2760	-0.2369
PA_STRUC	-0.6923	-0.2700
KRUG_MANUF	-0.6316	-0.0627
KRUG_SER	0.0536	0.3929
KRUG_PA	-0.6929	-0.0744
EXPY	0.3749	0.3400
MADEITALY	0.2561	0.3386
FINANC	-0.2741	-0.5725
CIVIC	0.5202	0.7162
HUMCAP	0.3029	0.1365
HUMCAP_ENTR	-0.6428	

Note: initial year (1992), average period (1992 – 2012), observations for *HUMCAP_ENTR* are available for the only Census year 2001.

Table 6 (A-D). Cross-regional regressions

(A)

Dependent Variable: Ecological Resilience				
Time period:	Initial Year		Average 1992-2012	
	(1)	(2)	(1)	(2)
MANUF_STRUC	0.8005*** (0.2242)	-	0.8149*** (0.1871)	-
SER_STRUC	-0.8213*** (0.2179)	-0.8251* (0.4972)	-0.6080*** (0.1427)	-0.15794 (0.3424)
PA_STRUC		-1.1927*** (0.2398)		-1.2258*** (0.5038)
Constant	0.4340 (0.6376)	0.4286** (0.1394)	0.3370 (0.5368)	0.3128*** (0.0831)
Observations	16	16	16	16
R^2	0.42	0.52	0.35	0.49
Prob > *F*	0.0072	0.0009	0.0018	0.0009
Root MSE	0.0860	0.0811	0.0908	0.0832

Note: Robust standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.

(B)

Dependent Variable: Ecological Resilience				
Time period:	Initial Year		Average 1992-2012	
	(1)	(2)	(1)	(2)
KRUG_MANUF	-2.1170***	-2.975***	0.2208	0.4138
	(0.6041)	(0.7639)	(0.9409)	(1.2424)
KRUG_SER	-0.8265	0.2419*	-0.4982	-0.3633
	(1.2688)	(1.4061)	(0.8558)	(1.0161)
KRUG_PA		1.7042**		-0.3475
		(0.7160)		(1.5032)
Constant	0.1643**	0.1133*	0.0100	0.0122
	(0.6376)	(0.0611)	(0.0878)	(0.0897)
Observations	16	16	16	16
R^2	0.41	0.52	0.03	0.04
Prob > *F*	0.0133	0.0169	0.5799	0.7791
Root MSE	0.0896	0.0843	0.1156	0.1199

Note: Robust standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.

(C)

Dependent Variable: Ecological Resilience								
Time period:	Initial year				Average 1992-2012			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
EXPY	0.0003	0.0003	-	-	0.0001	0.0001	-	-
	(0.0002)	(0.0003)			(0.0002)	(0.0001)		
BLOOD	1.2834*	1.1925*	1.5397*	1.3729*	1.3336*	0.6207*	1.3544*	0.5760*
	(0.6894)	(0.6704)	(0.7870)	(0.6232)	(0.68371)	(0.3796)	(0.6057)	(0.3013)
FINANC		-0.0075*		-0.0126*		-0.0508**		-0.0513**
		(0.0032)		(0.0065)		(0.0223)		(0.0232)
MADEITALY			0.0003	0.0002			0.0006	0.0005
			(0.0001)	(0.0001)			(0.0006)	(0.0005)
Constant	-0.5278*	-0.3544	-0.1087*	-0.1446	-0.4205*	0.2161	-0.1510*	0.4076*
	(0.2532)	(0.9208)	(0.0670)	(0.5908)	(0.2809)	(0.3284)	(0.0722)	(0.2490)
Observations	16	16	16	16	16	16	16	16
R^2	0.22	0.24	0.17	0.19	0.20	0.38	0.21	0.39
Prob > *F*	0.0433	0.0911	0.0692	0.1570	0.0669	0.0375	0.0426	0.0295
Root MSE	0.1030	0.1070	0.1060	0.1097	0.1046	0.0961	0.1040	0.0950

Note: Robust standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.

(D)

Dependent Variable: Ecological Resilience				
Time period:	Initial year		Average 1992-2012	
	(1)	(2)	(1)	(2)
HUMCAP	0.0709*	0.0298*	0.0405	0.0303
	(0.0410)	(0.0382)	(0.0586)	(0.0480)
HUMCAP_ENTR		-16.73***		-17.61***
		(4.730)		(4.689)
Constant	-0.5479	0.0414	-0.3651	0.0125
	(0.3938)	(0.3232)	(0.5339)	(0.4441)
Observations	16	16	16	16
R^2	0.10	0.43	0.08	0.42
Prob > *F*	0.0180	0.0070	0.0500	0.0073
Root MSE	0.1074	0.0885	0.1117	0.0885

Note: Robust standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.

Table 7. Moran's local index

Engineering resilience

Moran's Ii (resilience)

name	Ii	E(Ii)	sd(Ii)	z	p-value*
Vda	0.096	-0.053	0.323	0.460	0.323
Pie	0.060	-0.053	0.308	0.366	0.357
Lom	0.281	-0.053	0.255	1.307	0.096
Lig	-0.441	-0.053	0.256	-1.516	0.065
Ven	0.692	-0.053	0.258	2.881	0.002
Tre	1.278	-0.053	0.321	4.142	0.000
Fri	0.519	-0.053	0.302	1.894	0.029
Emi	0.621	-0.053	0.259	2.598	0.005
Tos	0.506	-0.053	0.268	2.086	0.018
Umb	0.095	-0.053	0.258	0.571	0.284
Mar	0.332	-0.053	0.248	1.550	0.061
Laz	-0.049	-0.053	0.246	0.015	0.494
Abr	-0.177	-0.053	0.254	-0.490	0.312
Mol	0.677	-0.053	0.278	2.626	0.004
Cam	0.906	-0.053	0.278	3.447	0.000
Pug	0.554	-0.053	0.290	2.092	0.018
Bas	0.778	-0.053	0.255	3.264	0.001
Cal	1.054	-0.053	0.278	3.972	0.000
Sic	0.570	-0.053	0.238	2.622	0.004
Sar	-0.159	-0.053	0.229	-0.464	0.321

Ecological resilience

Moran's Ii (resilience)

name	Ii	E(Ii)	sd(Ii)	z	p-value*
Pie	0.089	-0.067	0.277	0.563	0.287
Lom	0.126	-0.067	0.252	0.763	0.223
Lig	-0.464	-0.067	0.268	-1.482	0.069
Ven	0.218	-0.067	0.231	1.231	0.109
Emi	0.768	-0.067	0.252	3.311	0.000
Tos	0.579	-0.067	0.249	2.598	0.005
Umb	-0.303	-0.067	0.241	-0.980	0.164
Mar	0.076	-0.067	0.238	0.602	0.274
Laz	-0.010	-0.067	0.221	0.254	0.400
Abr	-0.146	-0.067	0.229	-0.345	0.365
Mol	0.299	-0.067	0.258	1.417	0.078
Cam	0.458	-0.067	0.262	2.001	0.023
Pug	-0.204	-0.067	0.281	-0.490	0.312
Cal	0.312	-0.067	0.270	1.405	0.080
Sic	0.228	-0.067	0.208	1.414	0.079
Sar	0.006	-0.067	0.204	0.359	0.360

*1-tail test

Note: Table 7 reports the Moran's I local index for engineering and ecological resilience.

Table 8 (A-D). Spatial ML estimation

(A)

Dependent Variable: Engineering Resilience				
Time period:	Initial year		Average 1992-2012	
	(1)	(2)	(1)	(2)
MANUF_STRUC	0.9139***	-	1.1611***	-
	(0.2460)		(0.3027)	
SER_STRUC	-2.5292***	-2.6459***	-1.3497***	-0.9951***
	(0.6694)	(0.5274)	(0.4191)	(0.4447)
PA_STRUC		-1.5255***		-1.4674**
		(0.2920)		(0.4197)
Constant	0.4230**	1.0363***	0.2565	0.8151***
	(0.1684)	(0.1907)	(0.1664)	(0.2561)
spatial dependence (γ)	0.7798***	0.5954*	0.6524**	0.4060
	(0.2072)	(0.3196)	(0.2935)	(0.4387)
σ^2	0.0053***	0.0033***	0.0063***	0.0067***
	(0.0017)	(0.0010)	(0.0020)	(0.0021)
Observations	20	20	20	20
Wald Statistics ($\chi^2_{(2)}$)	34.88	62.15	25.88	22.15
	[0.000]	[0.000]	[0.000]	[0.000]
Log Likelihood	23.133	28.265	21.655	21.447

(B)

Dependent Variable: Engineering Resilience				
Time period:	Initial year		Average 1992-2012	
	(1)	(2)	(1)	(2)
KRUG_MANUF	-1.9886***	-2.5519***	1.1331	0.8011
	(0.6617)	(0.7151)	(0.9601)	(1.0098)
KRUG_SER	4.0443***	2.9044*	-0.8631*	-1.2006*
	(1.2925)	(1.5172)	(0.5039)	(0.7454)
KRUG_PA	1.7017**	1.1787	-0.2374	-0.7308
	(0.8349)	(0.8863)	(1.0734)	(1.1269)
Constant	-	0.2299	-	0.1683
		(0.1595)		(0.1497)
spatial dependence (γ)	0.8992***	0.5733*	0.9006***	0.6418*
	(0.0879)	(0.3528)	(0.0820)	(0.3306)
σ^2	0.0088***	0.0083***	0.0137***	0.0136***
	(0.0028)	(0.0026)	(0.0044)	(0.0044)
Observations	20	20	20	20
Wald Statistics ($\chi^2_{(p)}$)	13.42	15.71	1.99	2.34
	[0.001]	[0.001]	[0.367]	[0.503]
Log Likelihood	17.288	19.156	12.893	14.073

Note: Estimates obtained by applying MLE. Standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%. Figures in brackets are p-values. Wald Statistics in (B) is equal to $\chi^2_{(2)}$ in (1) and $\chi^2_{(3)}$ in (2).

(C)

Dependent Variable: Engineering Resilience				
Time period:	Initial year		Average 1992-2012	
	(1)	(2)	(1)	(2)
EXPY	0.0810* (0.0462)	-	0.0184* (0.0106)	-
CIVIC	0.0122*** (0.0040)	0.0092*** (0.0033)	0.0133** (0.0061)	0.0146*** (0.0106)
FINANC	-0.0200* (0.0156)	-0.0157* (0.0078)	-0.0168* (0.0116)	-0.0155* (0.0111)
MADEITALY		0.0148* (0.0106)		0.0167* (0.0116)
Constant	-	-	-	-
spatial dependence (γ)	0.4942* (0.2353)	0.3338* (0.1987)	0.0490 (0.6408)	0.0463 (0.6469)
σ^2	0.0090*** (0.0028)	0.0097*** (0.0030)	0.0083*** (0.0026)	0.0080*** (0.0025)
Observations	20	20	20	20
Wald Statistics $(\chi^2_{(2)})$	12.12 [0.007]	10.52 [0.005]	14.93 [0.000]	15.71 [0.000]
Log Likelihood	18.547	17.828	19.521	19.809

(D)

Dependent Variable: Engineering Resilience				
Time period:	Initial year		Average 1992-2012	
	(1)	(2)	(1)	(2)
HUMCAP	0.0688** (0.0106)	0.0533 (0.0481)	0.0599** (0.0231)	0.0322 (0.0647)
HUMCAP_ENTR	-20.47*** (4.82)	-21.69*** (5.77)	-22.99*** (5.64)	-23.44*** (5.68)
Constant	-	0.1438 (0.3713)	-	0.2495 (0.5509)
spatial dependence (γ)	0.4531* (0.2353)	0.4437 (0.4511)	0.5408* (0.2931)	0.5578 (0.3838)
σ^2	0.0077*** (0.0024)	0.0076 (0.0024)	0.0080*** (0.0025)	0.0079*** (0.0025)
Observations	20	20	20	20
Wald Statistics $(\chi^2_{(p)})$	18.07 [0.000]	17.76 [0.000]	16.69 [0.000]	17.06 [0.000]
Log Likelihood	20.033	20.107	19.497	19.599

Note: Estimates obtained by applying MLE. Standard errors are in parentheses (). * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%. Figures in brackets are p-values. Wald Statistics in (D) is equal to $\chi^2_{(1)}$ in (1) and $\chi^2_{(2)}$ in (2).

Appendix

A1. Data description

Table 1. Data description (definition of variables and data sources)

Variable	Definition	Data Source
ENGRES	speed of adjustment linear VECM employment period 1992 – 2012	-
ECORES	degree of tolerance nonlinear STAR employment period 1992 – 2012	-
INDSTRUC	% of sector-specific added value (manufacturing, non-public services, PA)	Istat
KRUGIND	Krugman absolute specialization Index (manufacturing, non-public services, PA)	Istat
EXPY	*EXPY* for 38 product categories	Coeweb Istat
MADEITALY	*EXPY* for 17 product categories	Coeweb Istat
HUMCAP	average years of educational attainment	Istat
HUMCAPENTR	percentage of officers/managers and bureaucrats with a college degree	International IPUMS
CIVIC	% electoral participation to referendum	Istituto Cattaneo
BLOOD	n. of donations divided by the total population	AVIS
FINANCIAL	average interest rate at regional level	Bank of Italy

Table 2. Data description (summary statistics)

Variable	Mean	Stand. Dev.	Min	Max
MANUFSTRUC_1	0.2113	0.0716	0.1054	0.3340
MANUFSTRUC_2	0.1903	0.0633	0.0648	0.2905
KRUG_MANUF_1	0.0697	0.0348	0.0111	0.1398
KRUG_MANUF_2	0.0531	0.0322	0.0085	0.1254
SERSTRUC_1	0.2099	0.0254	0.1735	0.2639
SERSTRUC_2	0.2522	0.0439	0.1539	0.3580
KRUG_SER_1	0.0217	0.0159	0.0015	0.0463
KRUG_SER_2	0.0298	0.0315	0.0007	0.1057
PA_1	0.2101	0.0559	0.1255	0.3249

Table 2 (cont.). Data description (summary statistics)

Variable	Mean	Stand. Dev.	Min	Max
PA_2	0.2226	0.0552	0.1357	0.3311
KRUG_PA_1	0.0458	0.0301	0.0001	0.1147
KRUG_PA_2	0.0460	0.0287	0.0085	0.1084
EXPY_1	13527.76	764.25	11666.87	14661.56
EXPY_2	20848.36	1181.72	17836.60	22673.84
MADEITALY_1	9083.16	2221.53	3291.94	11590.27
MADEITALY_2	13825.98	3493.97	4350.22	17114.25
HUMCAP_1	7.79	0.5089	7.02	8.77
HUMCAP_2	9.01	0.3449	8.56	9.96
HUMCAPENTR	0.0155	0.0038	0.0101	0.0229
CIVIC_1	75.54	9.74	54.82	87.49
CIVIC_2	43.92	7.01	30.46	56.20
BLOOD	0.0519	0.0272	0.0142	0.0982
FINANC_1	18.99	1.02	17.62	21.04
FINANC_2	9.92	1.03	8.08	11.80

Note: All variables are referred to both the initial year of the period 1992 - 2012 (*1*) and to the average period over the same time span (*2*); the variable *HUMCAPENTR* is referred to the Census year 2001 and *BLOOD* to the average over the years 2006 – 2011.

Table 3. Product categories – Italian export basket

Code	Product description
AA01	Agricultural goods
AA02	Forestry goods
AA03	Fishing goods
BB05	Coal (excl. peat)
BB06	Oil and gas
BB07	Minerals
BB08	Other minerals
CA10	Food and taste
CA11	Drinks
CA12	Tobacco
CB13	Textiles
CB14	Cloths
CB15	Leather goods (excl. clothes)
CC16	Wood and wood products (excl. Furniture)
CC17	Paper and paper goods
CC18	Printed materials
CD19	Coke and refining goods
CE20	Chemicals
CF21	Pharmaceuticals
CG22	Rubber and plastics
CG23	Other non-minerals goods
CH24	Steel and steeling goods
CH25	Metal goods (excl. machinery)
CI26	Computer, optic and electronics
CJ27	Electrical machinery and other machineries
CK28	Machineries
CL29	Cars and trailers
CL30	Other transport goods
CM31	Furniture and design
CM32	Other manufacturing goods
DD35	Energy and gas
EE38	Wasting activities
JA58	Editing goods
JA59	Video, TV, Music and Cinema
MC74	Scientific and professional goods
RR90	Arts and entertainment
RR91	Libraries, archives and museums
SS96	Other personal services

Note: the 17 product categories of *MADEITALY* are: CA10, CA11, CB13, CB14, CB15, CE20, CF21, CI26, CJ27, CK28, CL29, CM31, CM32, JA58, JA59, RR90, RR91.

A2. Section II

1. Tests for nonstationarity

Employment Italy

A. Level

Augmented Dickey-Fuller test for unit root — Number of obs = 139

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.587	-3.497	-2.887	-2.577

MacKinnon approximate p-value for Z(t) = 0.4901

B. Growth

Augmented Dickey-Fuller test for unit root — Number of obs = 138

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.158	-3.497	-2.887	-2.577

MacKinnon approximate p-value for Z(t) = 0.0225

Employment North-West

A. Level

Augmented Dickey-Fuller test for unit root — Number of obs = 139

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.355	-3.497	-2.887	-2.577

MacKinnon approximate p-value for Z(t) = 0.6039

B. Growth

Augmented Dickey-Fuller test for unit root — Number of obs = 138

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.011	-3.497	-2.887	-2.577

MacKinnon approximate p-value for Z(t) = 0.0014

Employment North-East

A. Level

Augmented Dickey-Fuller test for unit root — Number of obs = 139

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-0.737	-3.497	-2.887	-2.577

MacKinnon approximate p-value for Z(t) = 0.8370

B. Growth

```
Augmented Dickey-Fuller test for unit root         Number of obs   =       138

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.498            -3.497            -2.887            -2.577
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Employment Centre

A. Level

```
Augmented Dickey-Fuller test for unit root         Number of obs   =       139

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -0.376            -3.497            -2.887            -2.577
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9141
```

B. Growth

```
Augmented Dickey-Fuller test for unit root         Number of obs   =       138

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.216            -3.497            -2.887            -2.577
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0006
```

Employment South

A. Level

```
Augmented Dickey-Fuller test for unit root         Number of obs   =       139

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.018            -3.497            -2.887            -2.577
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0332
```

B. Growth

```
Augmented Dickey-Fuller test for unit root         Number of obs   =       138

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.586            -3.497            -2.887            -2.577
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0060
```

2. LM-Test for autocorrelation

North-West

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	133.7259	81	0.00021
2	51.3178	81	0.99592

H0: no autocorrelation at lag order

North-East

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	195.4748	81	0.00000
2	127.7364	81	0.00072

H0: no autocorrelation at lag order

Centre

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	138.6906	81	0.00007
2	77.4037	81	0.59260

H0: no autocorrelation at lag order

South

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	128.8747	81	0.00057
2	70.4383	81	0.79272

H0: no autocorrelation at lag order

A3. Section III

1. Engle – Granger Cointegration Test

Piemonte

Source	SS	df	MS
Model	9.6436e+09	1	9.6436e+09
Residual	2.5188e+10	79	318832196
Total	3.4831e+10	80	435391670

Number of obs	80
F(1, 79)	30.25
Prob > F	0.0000
R-squared	0.2769
Adj R-squared	0.2677
Root MSE	17856

D.ehat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ehat L1.	-.5551857	.1009485	-5.50	0.000	-.7561187	-.3542527

Valle d'Aosta

Source	SS	df	MS
Model	31543879.2	1	31543879.2
Residual	84410842	79	1068491.67
Total	115954721	80	1449434.01

Number of obs	80
F(1, 79)	29.52
Prob > F	0.0000
R-squared	0.2720
Adj R-squared	0.2628
Root MSE	1033.7

D.fhat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
fhat L1.	-.534365	.0983481	-5.43	0.000	-.7301221	-.338608

Lombardia

Source	SS	df	MS
Model	4.4266e+10	1	4.4266e+10
Residual	8.6756e+10	79	1.0982e+09
Total	1.3102e+11	80	1.6378e+09

Number of obs	80
F(1, 79)	40.31
Prob > F	0.0000
R-squared	0.3379
Adj R-squared	0.3295
Root MSE	33139

D.ghat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ghat L1.	-.6130537	.0965608	-6.35	0.000	-.8052533	-.4208542

Liguria

Source	SS	df	MS
Model	1.7474e+09	1	1.7474e+09
Residual	7.1338e+09	79	90301667.8
Total	8.8812e+09	80	111014876

Number of obs	80
F(1, 79)	19.35
Prob > F	0.0000
R-squared	0.1967
Adj R-squared	0.1866
Root MSE	9502.7

D.hhat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
hhat L1.	-.3812174	.0866622	-4.40	0.000	-.5537142	-.2087206

Veneto

Source	SS	df	MS
Model	7.5672e+09	1	7.5672e+09
Residual	3.0467e+10	79	385655738
Total	3.8034e+10	80	475425329

Number of obs	80
F(1, 79)	19.62
Prob > F	0.0000
R-squared	0.1990
Adj R-squared	0.1888
Root MSE	19638

D.jhat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
jhat L1.	-.3086903	.0696875	-4.43	0.000	-.4473998	-.1699809

Trentino A.A.

Source	SS	df	MS
Model	699291285	1	699291285
Residual	4.7193e+09	79	59738345.6
Total	5.4186e+09	80	67732757.3

Number of obs	80
F(1, 79)	11.71
Prob > F	0.0010
R-squared	0.1291
Adj R-squared	0.1180
Root MSE	7729.1

D.ihat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ihat L1.	-.2619748	.0765697	-3.42	0.001	-.4143831	-.1095666

Friuli V.G.

Source	SS	df	MS
Model	1.6321e+09	1	1.6321e+09
Residual	4.6128e+09	79	58390128.7
Total	6.2450e+09	80	78061982.4

Number of obs	80
F(1, 79)	27.95
Prob > F	0.0000
R-squared	0.2614
Adj R-squared	0.2520
Root MSE	7641.3

D.lhat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
lhat L1.	-.5257282	.099438	-5.29	0.000	-.7236547	-.3278018

Emilia Romagna

Source	SS	df	MS
Model	1.2211e+10	1	1.2211e+10
Residual	3.8875e+10	79	492091291
Total	5.1086e+10	80	638577169

Number of obs	80
F(1, 79)	24.81
Prob > F	0.0000
R-squared	0.2390
Adj R-squared	0.2294
Root MSE	22183

D.mhat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
mhat L1.	-.4605007	.0924439	-4.98	0.000	-.6445057	-.2764958

Toscana

Source	SS	df	MS
Model	8.6257e+09	1	8.6257e+09
Residual	1.8592e+10	79	235339859
Total	2.7218e+10	80	340219104

Number of obs	80
F(1, 79)	36.65
Prob > F	0.0000
R-squared	0.3169
Adj R-squared	0.3083
Root MSE	15341

D.nhat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
nhat L1.	-.6390811	.1055619	-6.05	0.000	-.8491967	-.4289655

Umbria

Source	SS	df	MS
Model	1.1801e+09	1	1.1801e+09
Residual	3.4705e+09	79	43929780.8
Total	4.6505e+09	80	58131534.1

Number of obs	80
F(1, 79)	26.86
Prob > F	0.0000
R-squared	0.2537
Adj R-squared	0.2443
Root MSE	6628

D.ohat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ohat L1.	-.486064	.0937819	-5.18	0.000	-.6727323	-.2993958

Marche

Source	SS	df	MS
Model	2.0265e+09	1	2.0265e+09
Residual	4.8933e+09	79	61940256.1
Total	6.9198e+09	80	86496882.7

Number of obs	80
F(1, 79)	32.72
Prob > F	0.0000
R-squared	0.2929
Adj R-squared	0.2839
Root MSE	7870.2

D.phat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
phat L1.	-.5621945	.0982886	-5.72	0.000	-.757833	-.366556

Lazio

Source	SS	df	MS
Model	7.9298e+09	1	7.9298e+09
Residual	9.6739e+10	79	1.2245e+09
Total	1.0467e+11	80	1.3084e+09

Number of obs	80
F(1, 79)	6.48
Prob > F	0.0129
R-squared	0.0758
Adj R-squared	0.0641
Root MSE	34993

D.qhat	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
qhat L1.	-.1644605	.0646274	-2.54	0.013	-.2930982	-.0358227

Abruzzo

Source	SS	df	MS		
Model	1.7791e+09	1	1.7791e+09	Number of obs =	80
Residual	5.1915e+09	79	65714672.9	F(1, 79) =	27.07
				Prob > F =	0.0000
				R-squared =	0.2552
				Adj R-squared =	0.2458
Total	6.9706e+09	80	87131883.2	Root MSE =	8106.5

D.rhat	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rhat L1.	-.5343775	.1027023	-5.20	0.000	-.7388014	-.3299537

Molise

Source	SS	df	MS		
Model	45439164.9	1	45439164.9	Number of obs =	80
Residual	410880192	79	5201015.09	F(1, 79) =	8.74
				Prob > F =	0.0041
				R-squared =	0.0996
				Adj R-squared =	0.0882
Total	456319357	80	5703991.96	Root MSE =	2280.6

D.shat	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
shat L1.	-.1471086	.0497699	-2.96	0.004	-.2461731	-.048044

Campania

Source	SS	df	MS		
Model	9.5728e+09	1	9.5728e+09	Number of obs =	80
Residual	9.8336e+10	79	1.2448e+09	F(1, 79) =	7.69
				Prob > F =	0.0069
				R-squared =	0.0887
				Adj R-squared =	0.0772
Total	1.0791e+11	80	1.3489e+09	Root MSE =	35281

D.that	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
that L1.	-.1631724	.0588396	-2.77	0.007	-.2802896	-.0460551

Puglia

Source	SS	df	MS		
Model	7.7832e+09	1	7.7832e+09	Number of obs =	80
Residual	2.9458e+10	79	372891477	F(1, 79) =	20.87
				Prob > F =	0.0000
				R-squared =	0.2090
				Adj R-squared =	0.1990
Total	3.7242e+10	80	465520755	Root MSE =	19310

D.uhat	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
uhat L1.	-.4028284	.0881721	-4.57	0.000	-.5783307	-.2273262

Basilicata

Source	SS	df	MS		
Model	750287194	1	750287194	Number of obs =	80
Residual	1.9551e+09	79	24748701.2	F(1, 79) =	30.32
				Prob > F =	0.0000
				R-squared =	0.2773
				Adj R-squared =	0.2682
Total	2.7054e+09	80	33817932.3	Root MSE =	4974.8

D.vhat	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
vhat L1.	-.552415	.1003293	-5.51	0.000	-.7521156	-.3527145

Calabria

Source	SS	df	MS		
Model	2.9971e+09	1	2.9971e+09	Number of obs =	80
Residual	2.7983e+10	79	354219485	F(1, 79) =	8.46
				Prob > F =	0.0047
				R-squared =	0.0967
				Adj R-squared =	0.0853
Total	3.0980e+10	80	387255592	Root MSE =	18821

D.what	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
what L1.	-.1754528	.0603178	-2.91	0.005	-.2955124	-.0553933

Sicilia

Source	SS	df	MS		
Model	6.7323e+09	1	6.7323e+09	Number of obs =	80
Residual	3.7135e+10	79	470057286	F(1, 79) =	14.32
				Prob > F =	0.0003
				R-squared =	0.1535
				Adj R-squared =	0.1428
Total	4.3867e+10	80	548335528	Root MSE =	21681

D.zhat	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
zhat L1.	-.3265628	.0862899	-3.78	0.000	-.4983185	-.1548071

Sardegna

Source	SS	df	MS		
Model	6.4293e+09	1	6.4293e+09	Number of obs =	80
Residual	1.1211e+10	79	141913621	F(1, 79) =	45.30
				Prob > F =	0.0000
				R-squared =	0.3645
				Adj R-squared =	0.3564
Total	1.7640e+10	80	220506040	Root MSE =	11913

D.ahat	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ahat L1.	-.758702	.1127201	-6.73	0.000	-.9830657	-.5343384

2. Nonlinear Test results

Region	Lags	Transition variable (Δunempl. Ita)	H_0	H_{03}	Model
Piemonte	4	t-8	0.0009		LSTR1
Lombardia	3	t-3	0.0033	0.0022	LSTR2
Liguria	4	t-5	0.0004		LSTR1
Veneto	3	t-3	0.0009		LSTR1
Emilia Romagna	2	t-3	0.0005	0.0000	LSTR2
Toscana	3	t-2	0.0026	0.0003	LSTR2
Umbria	2	t-2	0.0009		LSTR1
Marche	3	t-1	0.0003		LSTR1
Lazio	4	t-4	0.0016		LSTR1
Abruzzo	4	t	0.0042	0.0019	LSTR2
Molise	8	t-5	0.0010		LSTR1
Campania	2	t-6	0.0022		LSTR1
Puglia	4	t-1	0.0017		LSTR1
Calabria	8	t-8	0.0013		LSTR1
Sicilia	4	t-5	0.0021		LSTR1
Sardegna	3	t-6	0.0022		LSTR1

Note: H_0 refers to the null hypothesis of linearity (p-value); H_{03} reports test results (p-value) on the null hypothesis of LSTR2 model (Teräsvirta, 2004). Nonlinearity has been rejected for Valle d'Aosta, Trentino A.A., Friuli V.G. and Basilicata. The maximum delay of the transition variable is 8 ($d = 8$).

3. LSTAR Estimation results

Region	Transition variable	C1	C2	γ	adj – R^2
Piemonte	t-8	0.04098***		10.44*	0.67
Lombardia	t-3	-0.10654***	0.03758***	5.25***	0.73
Liguria	t-5	-0.08514**		25.10**	0.66
Veneto	t-3	0.06131***		10.74**	0.70
Emilia Romagna	t-3	-0.05079***	0.15074***	16.28*	0.77
Toscana	t-2	-0.12072***	0.23614***	16.95**	0.72
Umbria	t-2	-0.06746*		5.08***	0.62
Marche	t-1	0.06669***		4.83***	0.64
Lazio	t-4	-0.03244***		2.36**	0.75
Abruzzo	t	-0.08306***	0.07065***	3.57***	0.74
Molise	t-5	-0.12344***		3.63**	0.67
Campania	t-6	-0.15964*		3.23**	0.65
Puglia	t-1	0.04304***		3.94***	0.82
Calabria	t-8	-0.14902***		3.43**	0.88
Sicilia	t-5	-0.07582***		2.94**	0.80
Sardegna	t-6	-0.0017*		6.28*	0.79

Note: Estimation results obtained by applying LSTR1 and LSTR2 specifications. * implies significance at 10%, ** implies significance at 5%, *** implies significance at 1%.