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Summary

The motivating research question of the present PhD thesis has been the following: it is not sufficient to choose a question that is interesting and important; you must also choose a question that you have some hope of answering (N.G. Mankiw, 1988). With this in mind, I have tried to shed light on the importance of studying recessions and recoveries at regional level, both in theory and in practice. In particular, the focus has been the development of some econometric tools for analyzing the Italian case. The reader could say if I have been able to provide some answers to this issue.

At least three reasons can sustain this perspective. First, the progressive improvement of data availability at infra national level provides a fertile ground for conducting empirical investigations. Second, the rooted divide showed by different regions within the same country sustains the search for more structured explanations, which can partially rely upon the asymmetric impact of booms and busts. Third, if regions react to fluctuations in a different way, then, modelling place-aware countercyclical monetary and fiscal policies may result more effective.

Three chapters constitute the main structure of this contribution. Chapter I reviews selected theoretical and empirical approaches dealing with regional evolution in order to identify recent developments and extensions incorporating spatial econometrics techniques. Chapter II investigates transient and permanent asymmetric effects of national-wide recessions across Italian regions during the last thirty years, by proposing the recent resilience framework as an helpful synthesis. Chapter III studies the determinants of the uneven cross-regional behaviour during crises and recoveries, by presenting two complementary econometric models, namely a linear vector error correction (VECM) model and a non-linear smooth-transition autoregressive (STAR) specification.

Some of the main results here obtained are: regions within the same country differ in terms of both shock-absorption and post-recession pattern; the broad impact of a common shock shall take into account temporary and persistent effects; differences in recessions and recoveries among areas can be motivated by some elements such as industrial structure, export propensity, human and civic capital, and financial constraints. Moreover, the presence of spatial interdependencies and neighbouring interactions can play a relevant role.

Moving from some of the results here presented, the desirable next step should be addressed towards a deeper analysis of the determinants of regional heterogeneity during recessions and recoveries, cross-country comparisons, the development of a more structured theoretical and empirical background, the assessment of the place-specific impact of countercyclical policies. These and other questions are left for future research.

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Regional recessions and recoveries: theories and empirical evidence

Abstract

The present work represents a survey in regional economics. Specifically, the main objective is a review of the literature and the design of the state of the art of the knowledge about regional recessions and recoveries. The regional resilience framework recently conceptualized offers a helpful starting point for broadening the research perspective on this topic. Selected theoretical and empirical approaches are presented in order to identify transient and permanent effects of national-wide recessions across regions. More recent developments are discussed together with possible future areas of research. Spatial econometrics extensions of empirical models are also presented for dealing with cross-sectional heterogeneity.

Keywords: regional business cycles, disaggregate fluctuations, hysteresis, asymmetric co-movement, dynamic-factor models, SpSVAR, non-linear models.

JEL classification: C32, C33, E24, E32, R11, R15.

I.Introduction

At least three reasons can motivate the renewed interest for regional topics. First, the presence of long-standing regularities like divergent patterns of convergence across territories and the rooted divide showed by different regions within the same country sustains the search for more structured explanations. Second, in the last two decades data availability at infra national level has substantially improved with detailed micro data now accessible more easily. Third, specific analytical tools such as spatial econometrics and techniques for dealing with cross-sectional heterogeneity have been progressively incorporated in empirical works favouring a deeper knowledge of geographical interdependencies.

In particular, the recent re-discovery of the concept of resilience among regional scientists (see, among others, the special issue of the *Cambridge Journal of Regions, Economy and Society*, 2010; Martin, 2012) has the value of revitalizing the study of regional recessions and recoveries both in theory and in practice. Although it does not represent a watershed in the existing literature, the resilience framework offers a new perspective for explaining the uneven geography of crises and the asymmetric behaviour of upturns. Not so surprisingly, then, an increasing number of contributions explicitly focus on this issue (Fingleton *et al.*, 2012; Fingleton and Palombi, 2013). Moreover, a larger amount of policymakers both in the US and in Europe is introducing resilience in the policy debate.

This survey aims to shed light on the more recent theoretical and empirical developments concerning the regional evolution of booms and busts. In the next pages, I will try to answer the following questions, recognizing the role of the resilience approach as a useful starting point. How can we identify the impact of economic shocks at infra national level? What are the determinants behind potential territorial differences during crises and recoveries? Can growth differentials across places be explained by dissimilar reactions to shocks? Do national countercyclical policies, monetary and fiscal, require to be integrated by region-specific elements to be more effective?

The remaining of the study is organized as follows. Section II briefly describes the distinctive features of the regional resilience framework and why it can provide an helpful starting point for bridging the gap between alternative traditions in the analysis of regional evolutions. The state of the art of theoretical contributions analysing regional shocks is surveyed in section III. Section IV deals with recent developments in the empirical literature. The final section offers some concluding remarks and possible avenues for future research.

II. Resilience and regional evolution

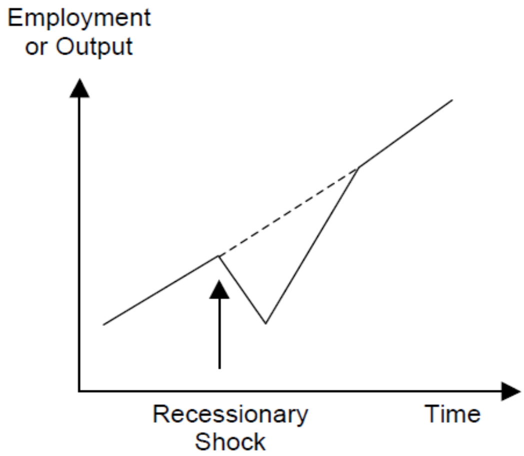
Resilience is a concept traditionally used in Ecology, Engineering and Physics for analysing the adaptability of particular ecosystems to given disturbances, denoting the resistance of a material or investigating some physical properties in presence of extraordinary events. In Economics, it will probably become soon a buzzword in the sense expressed by Robert Solow for commenting social capital: a new word for reshaping old ideas. Nevertheless, it can contribute to study recessions and recoveries at infra national level in a more integrated perspective, by bringing together two traditional and alternative strands of the literature dealing with the effects of economic shocks.

More specifically, two meanings of resilience have been recently proposed. Engineering resilience denoting the 'ability of a system to return to, or resume, its assumed stable equilibrium state or configuration following a shock or disturbance', and ecological resilience defining 'the scale of shock or disturbance a system can absorb before it is destabilized and moved to another stable state or configuration' (Martin, 2012). Both concepts share two common features: the presence of a shock hitting a particular (economic) system and the focus on the impact of the generic shock without précising the nature of the shock itself. Moreover, both concepts have been explicitly introduced for studying and comparing regional economic evolutions[1].

Engineering and ecological resilience, however, considerably differ in terms of both underlying paradigms and consequences arising from the shocks. Indeed, engineering resilience is based upon an implicit equilibrium dynamic where disturbances become relevant only for detecting temporary effects and identifying asymmetries between the bust-phase and the boom-phase across geographical units. Figure 1 illustrates this pattern.

[1] In addition, Martin (2012) suggests to integrate the twofold meaning of resilience with four common and related elements: i) the sensitivity of a regional economy to disturbances and disruptions (resistance); ii) the speed and extent of the recovery-phase (recovery); iii) the extent to which the regional economy re-defines its structure (re-orientation); iv) the degree of resumption of the growth path that characterised the regional economy prior to the shock (renewal).

Figure 1: Engineering Resilience



Source: Martin, 2012.

As a consequence, a particular fluctuation is able to impose a reduction in the pattern of a variable for a certain period, but its structural behaviour is re-established in the long run (bounce back or peak-reversion effect). In other words, a given economic system, such as a region, fluctuates around its normal level of growth. Disturbances are unpredicted accidents along this trajectory. According to this approach, the decline in GDP and employment does not influence an economy in a perpetual way. A place, such as a region or a city, then, is involved in a self-equilibrating continuous process.

Engineering resilience can be related to traditional business cycles models interested in assessing the transient impact of recessions and the characterizing elements of recoveries. As recently pointed out by Fatás and Mihov (2013), this way of analyzing business cycles dates back at least to Mitchell (1927) and Burns and Mitchell (1946), and it finds an evident application in the 'plucking' model of Milton Friedman (1964) and its extensions (Kim and Nelson, 1999)[2]. In this framework, recessions are extraordinary events which determines cycles, and there is a relation between a given recessionary event and its recovery. Moreover, the shock-absorption phase can be different (asymmetric) in the post-recessionary period.

Therefore, if we consider engineering resilience at regional level three aspects assume relevance. First, we need to correctly identify each disturbance (i.e. recession) and recovery in terms of both its timing and impact. In general, this means specifying a

[2] It is worth noting that Fatás and Mihov (2013) distinguish this approach, which is the basis for the NBER business cycle dating committee methodology, from the so-called trend-cycle approach (Lucas, 1975, 1977; Kydland and Prescott, 1982) where the fluctuations are symmetric and caused by small and frequent shocks affecting a long-run trend.

national-wide cycle on the basis of pre-defined criteria: endogenous like the adoption of Markov-switching dating methods or exogenous on the basis of the analysis of peaks and troughs (Hardin and Pagan, 2002).

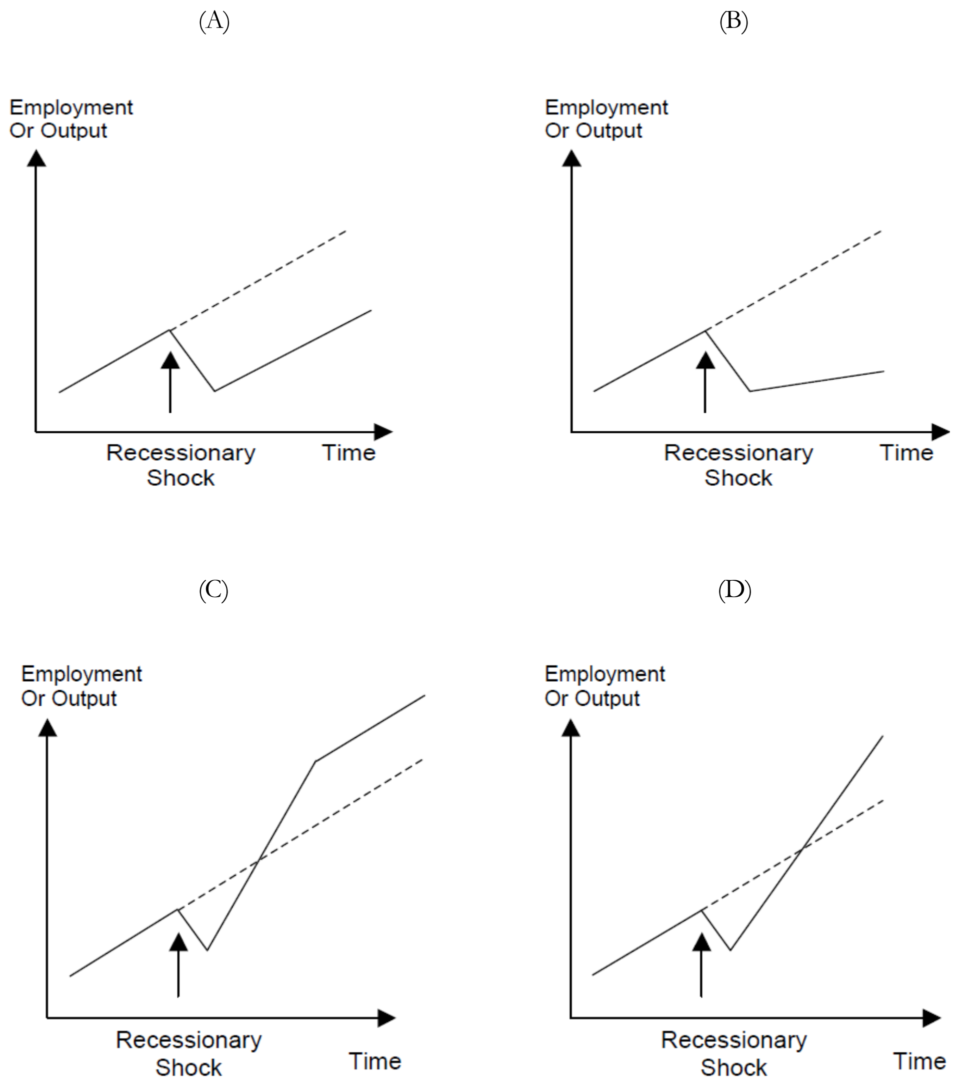
Second, it can be interesting to evaluate the overall effect of a given cycle by estimating its costs as cumulative losses in employment or GDP experienced during the cycle itself. And, variations in costs among areas within the same nation, captured by special-purpose indexes, can be associated to divergent resilient paths.

Third, it may result helpful to compare the effects of different cycles across time and space in order to provide a deeper knowledge of the geography of crises within a country. For example, regional differences in the timing of a recession (i.e. 'entry' and 'exit'), as documented by Owyang *et al.* (2005) for the US, can be conceived as a signal of engineering resilience. Regions affected longer than the national average, with anticipated entry and postponed exit, may be candidates to be less (engineering) resilient than the rest of the nation.

At the other end of the spectrum, ecological resilience relies upon the disequilibrium perspective firstly conceptualized by Nicholas Kaldor and Gunnar Myrdal along Keynesian lines. A particular system may develop along not-equilibrating trajectories depending on the initial conditions, history of shocks and agents' expectations. The presence of a long-run equilibrium, then, is neither assumed nor needed for describing a specific growth path. In this context, recessionary events act as substantive economic disturbances which are able to influence the future development of a given place. Hence, the adverse effects of a crisis become permanent not dying out over the periods and the memory of recessions matters for the future.

This definition of resilience is close to the rooted concept of hysteretic behaviour in Economics. Hysteresis, familiar among Economists since the past, can be defined as a 'situation where one-time disturbances permanently affect the path of the economy' (Romer, 2001). As a consequence, a peculiar economic system is not necessarily involved in self-adjusting dynamics, but it can experience multiple patterns in terms of post-recessionary evolution. In other words, the relation between long-run growth and shock-persistence becomes crucial. The four diagrams in figure 2 illustrate different possible post-recessionary patterns for an economy.

Figure 2: Ecological Resilience



Source: Martin, 2012.

A shock can shift downward the long-run potential of a system while maintaining a constant rate of growth (A). Or, the recessionary event may cause both a decline in the long-run growth and in its variation over time perpetuating a perverse cumulative process (B). Whereas the first case is typical of a territory experiencing a downsize in its structural evolution, the second represents a more negative situation in which a place will suffer prolonged adverse conditions.

Conversely, recovering after a recessionary shock can move the economy over its initial equilibrium with a constant rate after a certain period (C). Or, a given slump could stimulate positive reactions of a system addressing a long-term favourable cumulative process (D). Both situations can be described as processes of creative destruction *à la* Schumpeter, where the turning point is represented by the adverse shock.

The central element in this case is the relation between a given shock and the induced behaviour of the system under observation. In this sense, we are interested in defining the threshold of shock-absorption required to move from one equilibrium to another: this depends on both the magnitude of the shock and the specific vulnerability of the area[3]. And, it may also result important to highlight either which kind of equilibrium is achieved after a shock or what is the out-of-equilibrium pattern followed. Therefore, ecological resilience can be related to models characterized by multiple equilibria and non-linearity.

The concept of resilience, as it has been recently introduced in Economics, offers a worthwhile and quite intuitive stimulus to think hard when dealing with the impact of recessions across areas. On the one side, it combines both the temporary impact of disturbances on a given equilibrium level and the persistent out-of-equilibrium evolutions. On the other side, it provides further motivations for analysing the effects of shocks on economic growth following a place-specific approach (Cerra and Saxena, 2008; Cerra *et al.*, 2013).

Moreover, the intrinsic spatial nature of regional resilience sustains its role of additional informative element for assessing the real impact of monetary policy decisions. Indeed, in presence of regional heterogeneity, it becomes crucial to identify what are the reasons behind monetary policy effectiveness. In particular, a regional-based perspective analysing the three traditional channels associated to monetary policy, namely money, credit and bank lending, is able to look at the transmission of shocks in a more accurate way.[4] And, the analysis of the geographical unevenness during recessions and recoveries can act as a helpful starting point for proposing place-based countercyclical policies.

At this point, it is interesting to note how the resilience framework can result helpful for complementing the new directions pursued by the third generation of real business cycles models (Farmer, 2013; Plotnikov, 2013), which are aimed to introduce

[3] To be more precise, the specific nature of each shock plays an additional important role. To give an example, as demonstrated by Calvo and Reihnart (2002), currency crises are very different from banking crises if we consider both their origins and effects. While the former have direct implications for trade and public finances, the latter mainly influence credit availability and agents' expectations in financial markets.

[4] Traditionally, three channels of transmission of monetary policy have been identified. The *money channel* is the relation between a monetary shock and the variation of aggregate demand. The *credit channel* is the impact of monetary decisions on the broad credit market in terms of loans' availability *lato sensu*. The *bank lending channel* (or narrow credit channel) measures the impact of monetary policy on small banks and small and medium enterprises. For a more detailed discussion, see Owyang and Wall (2005).

multiple equilibria in unemployment[5]. These models rely upon assumptions peculiar to 'Old Keynesian Economics' (Farmer, 2008), where the natural rate hypothesis does not hold and deviations of the unemployment rate from its optimal value may be permanent. More on these models will be presented in the next section.

Asking what definition of resilience, engineering or ecological, is able to better describe the pattern of a given economy *ex post* with respect to a recessionary event is a sort of conundrum. Engineering resilience is probably more appropriated when we adopt a long-term equilibrium perspective and our data do not show particular breaks, while in presence of non-linear evolutions and if we recognize the possibility of modelling out-of-equilibrium economic relations, ecological resilience can result more suitable to analyse the phenomenon at hand.

In accordance with the unified approach heretofore discussed, the next section deals with the current state of the theory of regional recessions and recoveries, by considering both the mainstream equilibrium approach and some disequilibrium-based views.

III. Explaining regional evolution

Before proceeding to outline some of the main contributions dealing with regional recessions and recoveries three premises need to be discussed. First, the starting point of our analysis is a macroeconomic perspective and, therefore, we are interested in modelling the dynamic of aggregate variables leaving only a marginal role to the wide area of study developed by urban studies, economic geography and related disciplines[6]. Second, in the following pages we provide a selective review for the purposes of framing the analysis of resilience, recognizing that a synthesis of the theoretical contributions on regional evolution is both cumbersome and outside the boundaries of the present work. Third, the focus on the regional dimension is motivated by the need of understanding the asymmetric behaviour showed by regional fluctuations and the evidence of place-specific elements denoting business cycles (Owyang *et al.*, 2005; Wall, 2012).

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[5] The expression 'third generation' has been applied by Roger Farmer in its recent survey on endogenous real business cycles for distinguishing real business cycles models where multiple equilibria of unemployment are explicitly introduced from the 'second generation' (Benhabib and Farmer, 1994) in which there are multiple patterns of adjustment for reaching the same equilibrium level. The first generation refers to the pioneering contributions of Lucas (1977) and Kydland and Prescott (1982).

[6] It shall be noted, however, that some aspects hereafter discussed such as labor mobility and spatial interactions are common to both the approach here adopted and other disciplines. This point will be further clarified when explicitly addressed in the main text.

A simple Real Business Cycle (RBC) model is firstly introduced and discussed, highlighting its basic characteristics for dealing with economic shocks. More recent developments and some extensions for incorporating regional heterogeneity are also examined. Subsequently, a flexible framework for separating aggregate and regional fluctuations (Quah, 1996) is sketched providing some intuition for its empirical application and possible avenues for future research. Finally, regional hysteresis is presented within a recent RBC framework (Plotnikov, 2013), in combination with its possible causes and consequences.

III.1 (Real) Business Cycle models

Modern Real Business Cycle (RBC) models rely upon the dynamic stochastic general equilibrium approach firstly pioneered by Lucas (1975), Kydland and Prescott (1982) and King, Plosser and Rebelo (1988). Although they represent nowadays the mainstream theoretical view for analysing the economic behaviour of an aggregate economy, it shall be noted that they differ from the data-driven business cycle tradition historically referred to the NBER methodology (Fatás and Mihov, 2013). In particular, the latter is focused on the characterization of aggregate economic series by detecting expansions and contractions without assuming *a priori* that cycles are deviations from a given equilibrium level (i.e. overcoming the trend-cycle pattern). As a result, the discussion of (traditional) data-driven business cycle models is postponed to the empirical section.

The basic assumptions of a generic RBC model are the following: i) a representative-agent framework; ii) households and firms maximize their objective functions subject to given constraints; iii) the cycle-phase is determined by supply-driven Total Factor Productivity (TFP) shocks or neutral technology shocks (Justiniano *et al.,* 2010); iv) the natural rate hypothesis holds for unemployment; v) agents have rational expectations and markets clear. For a more detailed discussion, see Stadler (1994) and Farmer (2012).

As an example[7], let's consider a representative individual living for an infinite time period and having preferences described by the relation:

[7] The following set up is based upon the basic RBC model presented in King *et al.* (1988) and recently used by Roger Farmer (2013). Additional specifications will complicate the notation without modifying the basic insights we want to point out.

$$U = \sum_{t=o}^{\infty} \beta^t u(C_t, L_t)\,, \beta < 1$$

where β^t, C_t, L_t denote the discount factor, consumption and leisure, respectively. Firms produce according to the neoclassical production function

$$Y_t = A_t f(K_t, N_t)$$

where output (Y_t) results, as usual, from the combination of capital (K_t), labour (N_t) and total factor productivity (A_t). The law of motion of capital accumlation is

$$K_{t+1} = (1 - \delta)K_t + I_t$$

with δ denoting the depreciation rate of capital and I_t the gross investment. Every period two resource constraints are faced by the representative agent:

$$C_t + I_t \leq Y_t$$

$$N_t + L_t \leq 1$$

where the first relation relates total output to the sum of consumption and investment, and the second one constraints the allocation of time between labour and leisure to the total endowment of time T here normalized to 1. Additional constraints are: $L_t \geq 0$, $N_t \geq 0$, $C_t \geq 0, K_t \geq 0$.

Assuming that individual preferences are represented by a logarithmic utility function and production is expressed in the usual Cobb-Douglas form[8], the following system of equations allows to determine the time paths of output, consumption, capital, labour supply and total factor productivity[9]:

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[8] More specifically, the two restrictions on preferences must be: a) the intertemporal elasticity of substitution in consumption shall be invariant to the scale of consumption; b) the income and substitution effects linked to labour productivity growth must not interfere with labour supply. Apart from the logarithmic function, the other possible preferences form is the CES representation (King *et al*,.1988).

[9] In addition to equations (1.1)-(1.5), the following boundary conditions must hold: i) $K_0 = \overline{K_0}$; ii) $A_0 = \overline{A_0}$; iii) $\lim_{T \to \infty} E_t \left\{ \left(\frac{1}{1+\rho} \right)^T \frac{K_T}{C_T} \right\} = 0$, which are the initial condition for capital, the initial condition for TFP and the trasversality condition, respectively.

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}, \tag{1.1}$$

$$K_t = K_{t-1}(1-\delta) + Y_t - C_t, \tag{1.2}$$

$$\frac{1}{C_t} = E_t\left\{\frac{1}{1+\rho}\frac{1}{C_{t+1}}\left(1-\delta+\frac{\alpha Y_{t+1}}{K_t}\right)\right\}, \tag{1.3}$$

$$C_t L_t^{\gamma} = (1-\alpha)\frac{Y_t}{L_t}, \tag{1.4}$$

$$A_t = A_{t-1}^{\lambda}\exp(e_t). \tag{1.5}$$

Equations $(1.1) - (1.5)$ respectively identify: the production function, the capital accumulation relation, the agents' Euler equation, the first order condition for labour markets, and the evolution of total factor productivity. At this point, it is worth noting that total factor productivity follows a first order autoregressive process where the innovation has distribution $e_t \sim iid\,\mathcal{F}(0, \sigma^2)$. Moreover, in this context five parameters need to be specified, namely the rate of time preference (ρ), the elasticity of capital (α), the labour supply parameter (γ), the autocorrelation coefficient (λ) and the standard deviation (σ) of the disturbance e_t affecting Total Factor Productivity in equation (1.5).

In general, two main categories of disturbances are associated to the basic RBC model[10]. On the one hand, when consumption smoothing varies over time or unexpected changes in demand are faced by firms through inventories (Stadler, 1994), an adjustment occurs to re-balancing the evolution of a given economy. On the other hand, random fluctuations of the rate of technological change are able to hit the system under observation. However, only the second mechanism is defined as recession. More importantly, the evolution of an economy is characterized by the continuous presence of fluctuations triggered by the innovation process of TFP, which represent business cycle phases *per se*. In this context, each shock represents a transitory fluctuations in economic activity away from a permanent level (Morley and Piger, 2012). And, the link between recessions and recoveries is generally missed when applying RBC models.

[10] In reality, an additional source of innovation has been found to be relevant in these models: sunspots (Aziaridis, 1981). Sunspots shocks are typically referred to disturbances arising from agent's beliefs rather than fundamentals.

These basic intuitions still remain valid when additional features are introduced to the simple framework previously discussed. In particular, more recent Dynamic Stochastic General Equilibrium (DSGE) models deal with imperfect competition (Rotemberg and Woodford, 1995), taxes (Raurich *et al.*, 2006) and other sources of frictions (Smets and Wouters, 2007) such as labour market rigidities modeled in the spirit of the well-known matching models. In a complementary way, multiple steady-state equilibria have been also explored (Behnabib and Farmer, 1994) within the RBC framework, mostly driven by other forces (e.g. increasing returns-to-scale) than TFP shocks.

Three final comments can be pointed out. First, the underlying behavior of RBC models can be extended in principle to every economic system (i.e. region, city, etc.) without introducing *ad hoc* specifications. And, this has been the starting point of most of empirical analyses studying RBC at infra national level. In this case, the presence of cross-sectional dependence across places within the same country or the occurrence of spatial interactions are solved by modifying some empirical aspects (e.g. introducing heterogeneity in the error terms or filtering the series for each region). Second, as highlighted by Larry Summers (1986) some years ago, studying the business cycle by means of DSGE models does not necessarily implies providing a better understanding of the evolution of a given economy. This is particularly true when the parameterization shows some arbitrary components (Stiglitz, 2011). As we will see in the next section, the data-driven approach has maintained its explanatory power, though it does not rely upon sophisticated theoretical assumptions. Finally, RBC models do not allow to separate aggregate (i.e. national-wide) from disaggregate (i.e. place-specific) disturbances, limiting the possibility of jointly examining these two sources of business cycle dynamics.

III.2. Aggregate *vs* disaggregate fluctuations

The contemporaneous identification of aggregate shocks and disaggregate fluctuations is not a trouble-free task from a theoretical point of view, though it has been deliberately assumed as an objective by many empirical contributions (Carlino and Mills, 1998; Clark, 1998; Hamilton and Owyang, 2012). In general, disaggregate elements are considered as a byproduct of aggregate cycles of which they represent a natural complement. To give an idea of the importance of distinguishing aggregate from disaggregate cycles, in this sub-section the simple prototype model firstly presented by Danny Quah (1996) is discussed as its possible extensions.

Let's start by assuming that physical geography is defined as a probability space $(\mathbb{X}, \chi, \pi_x)$ with $\mathbb{X}$ denoting a set of generic (finite or infinite) dimensions (e.g. a circle, a plane, etc.), χ a relevant subset of $\mathbb{X}$, and π_x a probability measure which maps $\chi \rightarrow [0,1]$. The function $z(x)$ attributes specific characteristics z to a given location x, and it can be thought as the relation between a particular place (i.e. region or city) and its idiosyncratic features. In this sense, $z(x)$ is able to capture both time-invariant and time-varying regional elements.

Considering only labour input $l(x)$, regional output in a representative location x is given by the standard technology:

$$y(x) = f(l(x), z(x)), \tag{1.6}$$

where, as usual, $f_l = \frac{\partial f}{\partial l} > 0$ and decreasing in l denotes the productivity of labour.

Combining the relation (1.6) with the measure π_x on locations, we can obtain a probability relation for region-specific characteristics π_z, employment π_l and output π_y. The aggregate total output is obtained by summing up region-specific output for all locations:

$$\bar{y} = \int y(x)\pi_x(dx) = \int f\big(l(x), z(x)\big)\pi_x(dx), \tag{1.7}$$

and, consequently, the distribution of wages across regions can be easily obtained from:

$$w(x) = f_l\big(l(x), z(x)\big) = \frac{\partial f}{\partial l}\big(l(x), z(x)\big). \tag{1.8}$$

When labour is freely mobile across regions, in equilibrium, wages are equal whatever location we consider, and local labour markets clear. More formally,

$$\bar{w} = f_l\big(l(x), z(x)\big) = w(x), \tag{1.9}$$

$$\int l(x)\pi_x(dx) = 1. \tag{1.10}$$

where $\bar{w}$ is the common wage at aggregate level. Quah (1996) demonstrates that the following maximization problem

$$\sup_{l \in \mathbb{M}_+} \int f\big(l(x), z(x)\big)\pi_x(dx)$$
$$s.t \int l(x)\pi_x(dx) \leq 1 \tag{1.11}$$

is solved by a particular employment level l^* belonging to the set of non-negative measureable functions $\mathbb{M}_+ \in (\mathbb{X}, \chi)$.

For our purposes and without loss of generality[11], it can be assumed that the representative production function has the form $f(l, z) = l^\alpha z^\beta$, with z a scalar, $0 < \alpha < 1$ and $\beta > 0$. Therefore, the marginal productivity of labor is $w = f_l = \alpha l^{\alpha-1} z^\beta$, and local labor demand is $l = (\alpha/w)^{1/(1-\alpha)} z^{\beta/(1-\alpha)}$. As a result, the labour market clearing condition becomes:

$$(\alpha/w)^{1/(1-\alpha)} \int z^{\beta/(1-\alpha)} \pi_z(dz) = 1, \tag{1.12}$$

which, after some adjustments, gives the following equilibrium wage expression:

$$\bar{w} = \alpha\big(EZ^{\beta/(1-\alpha)}\big)^{1-\alpha}, \tag{1.13}$$

where E is the expectation operator and Z an artificial random variable.

In addition, in each region the employment optimal allocation is obtained by the relation

$$l^*(x) = (\alpha/\bar{w})^{\rho(\alpha)} z(x)^{\beta\rho(\alpha)}, \tag{1.14}$$

which positively depends on region-specific characteristics $z(x)$. Note that, in (1.14), $\rho(\alpha) = (1-\alpha)^{-1}$. When regions differ in terms of place-based features the same happens for employment, notwithstanding the aggregate and uniform wage. This idea is also reflected if we consider regional output in equilibrium, namely:

[11] For a more detailed discussion, see Quah (1996), which uses the same simplification for pointing out its main results.

$$y^*(x) = (\alpha/\bar{w})^{\alpha\rho(\alpha)} z(x)^{\beta\rho(\alpha)}, \tag{1.15}$$

that has been obtained by simply substituting equilibrium employment into the regional technology function. Once again, it can be noted that regional output is increasingly influenced by the location function $z(x)$.

From (1.15), and after some manipulations, the resulting aggregate output is $\bar{y} = \bar{w}/\alpha$ [12]. Substituting this expression and the wage relation described in (1.13) into (1.15), and applying a logarithmic transformation, equilibrium regional output is:

$$\log y^*(x) = -\alpha\rho(\alpha) \log \bar{y} + \beta\rho(\alpha) \log z(x). \tag{1.16}$$

Equation (1.16) states an important relation underlying regional output dynamic: two components, namely aggregate and disaggregate, are able to influence this pattern. As a consequence, national disturbances and place-specific fluctuations are both candidates for explaining regional evolutions. For instance, the positive/negative variation of regional GDP can be motivated by country-wide GDP movements or spatially-driven shocks such as seemingly regional Dutch disease phenomena (Papyrakis and Gerlagh, 2007), or both.

At this point, it is interesting to note that a crucial element of this framework is the almost complete independence between aggregate disturbances and disaggregate ones: common shocks cannot interfere with the locational process (i.e. the function z must be invariant to changes in $\bar{y}$), apart from national innovations which make z invariant (e.g. a vertical shift). In other words, what matters here is the possibility of disentangling the effects of regional shocks to national aggregates (given that national variables are simply the aggregation of regional ones), and *vice versa*.

The key element for applying this simple model in reality is the identification of a specific distribution which is able to discriminate across regions in terms of employment, output, income, and so on. And, this is the way pursued by Danny Quah for capturing both distribution dynamics and the impact of a given shock. Causal relations between national aggregate series (e.g. GDP) and regional dynamics (i.e. shifts in the region-specific

[12] Remembering the definition of *p*-norm for a random variable, the expression (1.13) of the aggregate wage can be rewritten as $\bar{w} = \alpha \|Z^\beta\|_{\rho(\alpha)}$, which gives aggregate output as $\bar{y} = \|Z^\beta\|_{\rho(\alpha)}^{-\alpha\rho(\alpha)} \cdot \|Z^\beta\|_{\rho(\alpha)}^{\rho(\alpha)} = \|Z^\beta\|_{\rho(\alpha)} = \bar{w}/\alpha$.

point distribution from one period to another) can be easily inferred in this set up. Moreover, it can be interesting to evaluate the magnitude of mobility dynamics showed by each region in response to a common shock.

Borrowing an expression used by Danny Quah, this model is simple and naïve. However, it has been presented here given as it is able to shed light on the way regions react to shocks arising from both national and regional level. In this direction, expanding this basic set up by introducing a different production technology, incorporating labour market frictions and further modeling labour mobility will probably enrich our knowledge about regional dynamics during crises and recoveries.

III.3. Regional hysteresis

Both approaches previously introduced have the merit of analysing the impact of shocks on the evolution of a given economic system, though they are quite different in terms of initial assumptions and main results. However, they share a common feature: shocks are transient events along the path of a particular economy. In other words, unexpected disturbances such as recessions will affect regional evolution (e.g. employment or GDP) in a temporary way, without altering its underlying behaviour[13].

Alternatively, one possible way of studying the persistent effect of shocks has been traditionally associated to the idea of hysteresis (Blanchard and Summers, 1996; Ball, 2009). In particular, early contributions on this topic have been explicitly committed to find an explanation for long-lasting dynamics such as the high unemployment rate showed by some countries in Europe (Blanchard *et al.*, 2006)[14]. Although hysteresis-based explanations have been applied to justify several empirical regularities, its main usage can be ascribed to the persistence of unemployment at both national and regional level.

A large set of arguments has been proposed in order to explain why an economic system can be locked-in as a consequence of path-dependent trajectories (Setterfield, 2009). Focusing on employment evolution, for instance, one-way migration of people and ideas can perpetuate a depressing disequilibrium process widening divergences among places in terms of labour attractiveness (Burrdige and Gordon, 1981; Martin and Sunley, 1998).

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13 In principle, the Quah's model could incorporate path-dependent effects by specifying the location process or modelling aggregate and disaggregate disturbances in a different manner, but such extensions are not present in the literature, at least to our knowledge, and we discard these hypotheses.

14 Despite hysteresis is traditionally referred to a negative pattern (e.g. a structural rise in unemployment), it does not imply *a priori* a negative relation between future outcomes and past events. In this sense, ecological resilience implicitly recognizes the presence of both positive and negative long-lasting relations.

Moreover, a decline in the capital stock (human and physical) caused by an adverse event can explain the long-lasting impact of a recession (Rowthorn, 1999)[15]. Insider-outsider effects in wage determination, labour hoarding and labour market tightness, firing costs and institutional rigidities are some of the additional reasons behind hysteresis (for a more detailed review, see Røed, 1997).

More recently, hysteresis-based explanations have represented the basis for analysing the persistent effect of recessions and, as a direct consequence, of jobless recoveries (Calvo *et al.*, 2012)[16]. In this sense, it is interesting to describe how and why a given economy is not able to rebalance its pre-shock employment level. And, whether or not a particular recessionary moment can shift the economy toward a different equilibrium, where unemployment may result higher/lower. This seems another way to look at the disequilibrium effects induced by recessions, familiar to the Keynesian tradition.

Let's investigate this aspect by means of the 'Old-Keynesian version of the RBC model', which is a recent extended version of the RBC model presented in the sub-section III.1. Now, incomplete factor markets are introduced together with the hypothesis that there are frictions in the labour supply curve (Plotnikov, 2013)[17]. The initial assumptions of the basic RBC model are still valid and, therefore, equations (1.1) - (1.3) and (1.5), and the three boundary conditions (see, footnote 9) remain unchanged. What changes now is the determination of the equilibrium wage, which in this case is obtained by a search mechanism, instead of in a competitive market.

Equation (1.4) can be divided in

$$\omega_t = C_t L_t^{\gamma}, \tag{1.17a}$$

$$\omega_t = (1-\alpha)\frac{Y_t}{L_t}, \tag{1.17b}$$

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15 The relationships between capital shortage and unemployment is an evergreen issue within the economic debate and it is mainly focused on the inelasticity of factor substitution between labour and capital (Bean, 1989; Rowthorn, 1999; Stockhammer and Klaar, 2011).

16 A complementary perspective in the study of hysteresis is the connection between 'sheltered economies' and lack of convergence recently re-proposed by Rodriguez Posé and Fratesi (2007). Basically, these authors link the poor performance of some areas (e.g. regions) to their inability of catching up with national evolution.

17 More precisely, in what follows it is applied the notation used in Farmer (2012).

with ω_t denoting real wage. In this context, the relation (1.17a) does not hold, given the incompleteness of labour market, and it is necessary to solve the system of equations by pursuing a different route.

As in Farmer (2010), the total workforce L_t can be thought as the sum of production workers X_t and recruiters V_t. Each recruiter is able to hire a fraction θ_t of workers, namely $L_t = \theta_t V_t$, with the parameter θ_t (i.e. the recruiting technology) determined in aggregate and representing the degree of congestion in the labour market. As a consequence, the relation (1.1) can be rewritten as

$$Y_t = A_t Z_t K_t^{\alpha} L_t^{1-\alpha}, \tag{1.18}$$

where $Z_t = \left(1 - \frac{1}{\theta_t}\right)^{1-\alpha}$ denotes the externality arising from the recruiting mechanism.

Under the hypotheses discussed in Farmer (2010), it can be showed that $\theta_t = 1/\bar{L}$, with $\bar{L}$ the average employment level and, therefore, the above relation becomes

$$Z_t = (1 - \bar{L})^{1-\alpha}, \tag{1.19}$$

capturing a labour market externality. In other words, the relation (1.19) states that the higher the employment level is, the more difficult is to find workers to be employed. And, more importantly, $\bar{L}$ represents the specific steady-state employment level.

In this case, the model is closed by assuming that individuals consume on the basis of adaptive expectations based upon their permanent income as in Friedman (1957). More precisely, consumption is defined as a proportion of the future income earned by individuals, namely

$$C_t = \varphi Y_t^P, \tag{1.20}$$

where permanent income is given by the expression

$$Y_t^P = (Y_{t-1}^P)^{\vartheta} Y_{t-1}^{1-\vartheta} \exp(e_t^b), \tag{1.21}$$

with the parameter ϑ denoting the degree of adaptation in expectations driven by the current income, and $e_t^b \sim iid\, \mathcal{F}(0, \sigma^2)$ a belief shock[18].

Evaluated at the steady state, equations (1.1) - (1.3) and (1.5) allow to obtain the relations:

$$\frac{\bar{C}}{\bar{K}} = \frac{\rho+\delta(1-\alpha)}{\alpha}, \tag{1.22}$$

$$\frac{\bar{Y}}{\bar{K}} = \frac{\rho+\delta}{\alpha}, \tag{1.23}$$

$$\frac{\bar{C}}{\bar{Y}} = \frac{\rho+\delta(1-\alpha)}{\rho+\delta}, \tag{1.24}$$

where the overscore characterizes variables at the steady state. Moreover, the following constraints must hold:

$$\varphi \equiv \frac{\rho+\delta(1-\alpha)}{\rho+\alpha}. \tag{1.25}$$

This model is solved by combining equations (1.2), (1.3), (1.5), (1.17b), (1.18), (1.20), (1.21) together with the initial conditions (see, footnotes 9 and 18). For our purposes, it is worth pointing out that this framework identifies the equilibrium employment at the steady-state as a path-dependent variable, which is driven by the adaptive agents expectations. To give an example, when shocks are absent the steady-state value of employment depends on the starting belief about permanent income, namely Y_0^P. However, the presence of shocks, either TFP recessions or simple variations in consumption smoothing, pushes the system towards a different steady-state, with a diverse level of employment (i.e. unemployment) achieved by a shift in expectations on permanent income.

Although this new version of the RBC model suffers from the same shortcomings yet identified within the RBC framework and it does not explicitly deal with regional interdependencies, it allows to consider the long-term effect of exogenous shocks in terms of employment/unemployment. Indeed, linking the equilibrium level to expectations based

[18] Note that, since Y_t^P is a state variable, closing the model requires the following additional initial condition $Y_0^P = \bar{Y}^P$.

upon future income and considering incomplete labour markets, the Plotnikov's model is able to relate unexpected disturbances to the persistent behavior of unemployment. In other words, the concept of hysteresis is a crucial element in this context where equilibria are path-dependent. Being a quite new approach in the literature, the 'Old-Keynesian' perspective applied to RBC models needs further research. Nevertheless, the first empirical attempts provide supporting results and a possible starting point for extending the analysis at infra national level.

IV. The empirics of regional recessions and recoveries

Since the seminal contribution of Burns and Mitchell (1946), and probably even before, the study of business cycles at both aggregate and disaggregate level has been mostly an empirical task. Indeed, macro econometricians have been deeply involved in dating, measuring, disaggregating and explaining the evolution of output series such as GDP or employment. Therefore, the detection of turning points in economic activity and the reaction of a given economic system to unexpected disturbances have been primary challenges faced by practitioners. As a result, a multifaceted spectrum of techniques has been proposed in this context. For a more detailed discussion, see Stock and Watson (2003) and De Haan *et al.* (2008).

In this section, we select three main areas of empirical research focusing on regional recessions and recoveries[19]. First, the state of the art of the data-driven approach is surveyed by discussing both some well-known measures (i.e. filters and leading indicators) in combination with the bulk of this area of study, namely the Markov-based perspective firstly pioneered by Hamilton (1989). Second, two structural linear models are presented, a (spatial) structural VAR and a simple version of the regional dynamic latent factor model (Owyang *et al.*, 2009). Finally, nonlinear issues are addressed by using the basic version of the Multiple-Regime Smooth-Transition Autoregressive Model (MRSTAR) discussed in van Dijk and Franses (1999).

For each empirical area, our lens are based upon the four objectives of macroeconometrics indicated by Stock and Watson (1999): describing and summarizing macroeconomic data, making forecasts, quantifying the true structure of a given economy,

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[19] Given our purposes, we do not consider here the burgeoning literature on panel VAR which represents the new frontier for the empirical assessment of DSGE models. For more on this topic, see the detailed review in Canova and Ciccarelli (2013).

advising policy makers. Moreover, given the regional focus of this work, contributions dealing with spatial effects within these three area are also reviewed.

IV.1. Measuring and detecting regional cycles

One popular way of investigating the behaviour of output series like GDP, employment and industrial production is based upon the detection of the degree of synchronization across countries/regions or the identification of possible co-movements between output fluctuations. In general, this approach follows three steps. First, a decomposition of the trend-cycle pattern is made by means of non-parametric filters. Second, a measure of correlation is used for relating what is obtained from the previous step. At the end of the second step, synchronization and co-movements are eventually found out. Finally, the correlation measure derived from the second step is the dependent variable of cross-section or panel regressions, which have the objective to explain the causes behind the particular behaviour emerged from the data[20].

The well-known Hodrick – Prescott high-pass filter is one of the most applied filtering approach in this field. Basically, it derives the trend component by minimizing the observed deviations from the trend series, subject to some smooth parameters. The Baxter – King or band-pass filter combines an high-pass filter with a low-pass filter in order to capture both high and low frequencies at predefined cut-off points. A similar band-pass procedure is applied by the Christiano – Fitzgerald filter. In a quite different way, the Phase Average Trend filter (Boshan and Ebanks, 1978) introduces an algorithmic for detecting cyclical turning points in the series and connecting the mean value between each cyclical peak for estimating the trend pattern. All these filtering procedures allow to separate cyclical fluctuations and trend dynamic, providing a first approximation of the incidence of disturbances.

Once de-trended series have been obtained, the degree of business cycle synchronization across units and possible co-movements are investigate by measuring correlation *lato sensu*. A simple way of doing this is to apply the (Pearson) correlation coefficient for each variable of interest. More articulated indexes have been proposed such as the dynamic co-spectrum measure of Croux *et al.* (2001) and the concordance index of Harding and Pagan (2002). In particular, the latter is able to capture co-movement by

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[20] More precisely, an independent additional phase has been progressively pursued within this framework, namely the estimation of the amplitude and the duration of recessionary events. As a consequence, several speculations on the costs of different recessions have been proposed in the recent literature (Claessens *et al.*, 2009; Fatas and Mihov, 2013).

counting the percentage of the time where two series are in the same phase of the business cycle.

The natural subsequent step is analysing what are the causes behind synchronization and co-movements. For instance, Belke and Hein (2006) study the evolution of synchronization across European regions (NUTS II) and its determinants, by running a panel regression where the dependent variable is the de-trended synchronicity index obtained by applying the Hodrick - Prescott filter. In a complementary way, Artis *et al.* (2011) extend this approach by introducing spatial effects through the estimation of a spatial panel model.

A quite different approach has been developed by Stock and Watson (1989) for defining the so-called leading indicators for the US States (for an extended version, see Crone and Clayton-Matthews, 2005). More specifically, the Stock and Watson's model relates the evolution of a given economy to a (unobserved) dynamic factor model defined by the following dynamic equations:

$$\Delta X_t = \alpha + \beta(\mathrm{L})\Delta c_t + \mu_t, \tag{1.26}$$

$$\gamma(\mathrm{L})\Delta c_t = \delta + \eta_t, \tag{1.27}$$

$$D(\mathrm{L})\mu_t = \epsilon_t, \tag{1.28}$$

where the system is composed by a measurement equation (1.26) and two transition equations (1.27) - (1.28). X_t, c_t and L denotes the observed variable, the common state of the economy to be estimated and the lag operator, respectively. $\mu_t, \eta_t, \epsilon_t$ are idiosyncratic components. The common factor c_t is estimated by using a Kalman filter and the resulting leading indicators (or coincidence indexes) for each State capture the relation between the national common dynamic (i.e. the reference point) and the State-level result.

Probably, the most widely used approach for measuring and dating recessions and recoveries is the Markov-switching model evolved along the lines tracing back to Hamilton (1989)[21]. Here, business cycle turning points are linked to the mean growth rate of a

[21] The Markov-switching model is a nonlinear representation. It has been placed here (and not in the subsection IV.C) given that it is part of the data-driven approach, rather than of the structural nonlinear modeling perspective. The basic version has been extensively modified and integrated. For new developments in this context, see Chauvet and Yu (2006), Kim, Piger, and Startz (2008), Guerin and Marcellino (2011), Morley and Piger (2012).

parametric statistical time series model. Let's y_t identifies economic activity (GDP or employment), a simple Markov-switching model results from the combination of the following relations:

$$y_t = \mu_{S_t} + \varepsilon_t, \tag{1.29}$$

$$\mu_{S_t} = \mu_0 + \mu_1 S_t, \tag{1.30}$$

with $\mu_1 < 0$ and $\varepsilon_t \sim N(0, \sigma^2)$ the stochastic innovation. In a two-regimes context, the state variable $S_t = \{0,1\}$ captures the distinction between recessions and recoveries. At this point, note that S_t is an unobserved variable and, therefore, we need to specify its transition process. For instance, assuming that S_t follows a first-order two-state Markov chain, transition probabilities are $\Pr[S_t = j \mid S_{t-1} = i] = p_{ij}$.

This basic version of the Hamilton's model is able to unveil the main aspects of this approach. In particular, according to the specific transition probabilities a switch of S_t (from 0 to 1) implies a variation in the growth rate of economic output from μ_0 to $\mu_0 + \mu_1$. As a consequence, the model estimates the probability that a country/region is in recession (expansion) at a given point in time.

This procedure has been successfully applied for investigating the time of entry and exit of each State in the US for different national-wide recessions (Owyang *et al.*, 2005). Also, these authors have estimated and compared the State-specific probability of remaining in a recession or recovery phase. More recently, Hamilton and Owyang (2012) have extended the Markov-switching approach at infra national level by disaggregating regions (US States) in different clusters with similar business cycle characteristics. Using Bayesian posterior inference, the authors provide additional evidences on the geographical unevenness of recession in the US.

The data-driven approach *lato sensu* briefly reviewed here has been the merit of describe and summarize macroeconomic data in a quite appropriate way. Not so surprisingly, then, it represents the starting point for the NBER business cycle dating methodology and the leading indicators used by both the Conference Board at international level and the Federal Reserve System within the US. The correct identification of the underlying structure of a given economy and the set of policy proposals associated to this perspective are positive elements in favour of its adoption. The forecasting accuracy of data-driven models at regional level, and in particular of the Markov-switching model needs further investigation, given that it is a quite recent issue in regional applications (Owyang *et al*, 2012)[22].

IV.2. Structural linear models

Clark (1998) developed a structural linear vector autoregression (SVAR) model for disentangling national, regional and industry-specific employment fluctuations for the US case over the period 1947 - 1990. Using matrix notation, the original Clark's model assumes the following form:

$$\mathbf{Y}_t = \sum_{j=1}^{J} \mathbf{\Gamma}_j \, \mathbf{Y}_{t-j} + \mathbf{e}_t, \tag{1.31}$$

$$e_{r,t} = \gamma_r c_t + \sum_i \tilde{\alpha}_{r,i} \mu_{i,t} + u_{r,t}, \tag{1.32}$$

$$e_{i,t} = \gamma_i c_t + \mu_{i,t} + \sum_i \tilde{\beta}_{r,i} u_{r,t}, \tag{1.33}$$

where $\mathbf{Y}_t$ is the vector $(R+I) \times 1$ of both region and industry employment growth rates, $\mathbf{\Gamma}_j$ the coefficient matrix to be estimated and $\mathbf{e}_t$ the vector error term. Equations (1.32) - (1.33) represent the structure of the error terms for regions (r) and industries (i). c_t, $\mu_{i,t}$, $u_{r,t}$ identify the innovations at national, industry and regional level, respectively.

In the identification process, the coefficient γ (i.e. capturing the impact of the common national shock) has to be estimated, while the parameters $\tilde{\alpha}_{r,i}$ and $\tilde{\beta}_{r,i}$ represent constant values. In particular, the coefficient $\tilde{\alpha}_{r,i}$ (i.e. capturing the industry-specific shock on each region) is set equal to the employment share of industry i in region r's total employment; and, the coefficient $\tilde{\beta}_{r,i}$ (i.e. capturing the region-specific shock on each industry) is set equal to the employment share of region r in industry i's total employment. Intuitively, the above error structure allows to introduce a distinct source of fluctuation (i.e. national) and two related disturbances arising from regions and industries[23].

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[22] To our knowledge, the model developed by Owyang *et al.* (2012) is the first application of the data-driven approach for forecasting purposes. The authors integrate aggregate and disaggregate predictors in a probit model estimated by applying the Bayesian model averaging (BMA) approach. Their main result is the additional informative content in terms of forecasts, both in-sample and out-sample, achieved by considering regional elements.

[23] As usual in SVAR models, an identifying restriction is required in order to estimate the above relations. For this reason, Clark (1998) applies the restriction that the variance of the national shock has to be equal to one.

The resulting SVAR model has been estimated by considering both fixed (at a given point in time) and time-varying impact coefficients $\tilde{\alpha}_{r,i}$ and $\tilde{\beta}_{r,i}$. In the first case, estimation is conducted by applying the unweighted method of moments (MOM); while in the time-varying specification it has been adopted the second moments procedure implied by the model. Basically, the latter relies upon the estimation of a system of nonlinear equations relating observed time series to the cross products of VAR residuals. As usual, impulse-response functions and forecast error variance decomposition are two traditional ways of examining model results.

In principle, the introduction of SVAR models for analyzing regional recessions and recoveries can appear a worthwhile task: in this sense, see, among others, the contribution of Carlino and De Fina (1998). However, modeling spatial interdependencies within the SVAR framework means amplifying the over-parameterization issue traditionally associated to these models. In a pair of interesting papers, Valter di Giacinto (2003 and 2010) develops and estimates a spatial version of the SVAR model (SpVAR)[24], which explicitly considers simultaneous regional interdependencies across geographical areas.

More precisely, the basic idea behind the SpVAR model is the assumption that the impact of region-specific shocks is deeper in neighboring regions and it progressively decreases as geographical distance increases (Di Giacinto, 2003) [25]. Formally, two kinds of constraints need to be specified for the identification of the SpVAR model: i) standard (non-spatial) constraints linked to the recursive ordering of the endogenous variables; ii) restrictions on the spatial effects coefficients derived from the underlying spatial structure captured by (the usual) spatial weight matrices (Di Giacinto, 2010). Once identified, the SpVAR can be estimated by applying Full Information Maximum Likelihood (Amisano and Giannini, 1997).

In recent years, the dynamic-factor model (Forni *et al.*, 2000) has been increasingly applied as an alternative specification to study the (linear) evolution of economic series such as GDP or employment at infra national level. Here, the regional extension proposed by Owyang *et al.* (2009) is briefly discussed. More specifically, let's consider the following relation:

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[24] A different spatial approach to VAR models has been proposed by Beenstock and Felsenstein (2007).

[25] In the SpVAR model, Di Giacinto maintains the three assumptions of Carlino and De Fina, namely: i) region-specific shocks contemporaneously affect only the region of origin, although they are allowed to spill over into other regions during future periods; ii) monetary policy actions and shocks to macro variables are assumed to affect regional income with at least a one-period time lag; iii) macro control variables are not contemporaneously affected by shocks in the remaining variables in the model and do not affect each other. For a more detailed discussion, see Di Giacinto (2003).

$$X_{i,t} = \lambda'_i F_t + e_{i,t}, \qquad (1.34)$$

where $X_{i,t}$ is a specific observation in region i at time t, the term $\lambda'_i F_t$ is the common component characterizing $X_{i,t}$, and $e_{i,t}$ the idiosyncratic element. The overall number of common factors is defined by the vector $F_t = (F_{1t}, \dots, F_{rt})'$ and it can be interpreted as the set of national-wide disturbances affecting each regional pattern. The vector of factor loadings, namely $\lambda_i = (\lambda_{i1}, \dots, \lambda_{ir})'$, detects the impact of each common factor on regional evolution.

One way of estimating the model in (1.34) is applying the principal component approach to determine the factor matrix $\mathbf{F}$ and the factor loading vector $\boldsymbol{\lambda}$. In a set of recent papers (Chauvet and Hamilton, 2005; Chauvet and Piger, 2008 and 2012), the basic dynamic-factor model has been integrated with a Markov-switching structure of the common component. Despite such extensions, however, what is relevant in this case is the possibility of distinguishing two sources of shocks interfering with regional dynamics. For a given recessionary event, then, the different magnitude registered by national-wide and place-specific shocks is explicitly identified in this set up by modeling the dynamic common factor in an appropriate way.

Moreover, the introduction of spatial elements in this framework is possible through the factor loading vector. In concrete, Owyang *et al.* (2009) estimate different spatial Durbin models taking the form

$$\lambda'{}_i^{\,j} = \rho W \lambda'{}_i^{\,1} + A\beta_0 + Z\beta_1 + WZ\beta_2 + v, \qquad (1.40)$$

where $\lambda'{}_i^{\,j}$ is the vector of estimated factor loadings affecting region i, W is the canonical spatial weight matrix, A and Z are matrices of covariates and $v \sim N(0, \sigma_I^2)$ is the error term. Once defined the spatial structure of the model (i.e. specifying the spatial matrix), consistent estimates of the spatial autocorrelation coefficient ρ can be obtained by applying Maximum likelihood[26].

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26 More articulated version of the spatial generalized dynamic-factor model have been recently proposed (Lopes *et al*, 2011).

Structural linear models offer a sounded approach to deal with macroeconomic data, given as they are focused on detecting and estimating structural relations between economic series. As we have seen, their application at regional level provides a fruitful area of research, though further contributions are required. Both the SVAR model and the dynamic-factor approach allow to separate different sources of shocks. Moreover, the spatial version of the SVAR introduces the possibility of cross-sectional interactions among areas.

The forecasting performance of these models (Chauvet and Potter, 2012) is an open question in the literature: whether their in-sample forecasting ability seems quite affordable, the out-sample one shows some limitations. In general, SVAR models are good predictors in normal times, but during recessions they do not provide accurate forecasts. Conversely, dynamic-factor models do quite well in forecasting during recessions (see, among others, Stock and Watson, 2003; Marcellino, Stock and Watson, 2003).

IV.3. Recent nonlinear developments

Whether national and regional dynamics are better approximated by a non-linear pattern instead of a linear one is an open debate within the theoretical and empirical literature studying recessions and recoveries (Chauvet and Potter, 2012; Morley *et al.*, 2012; Ferrara *et al.*, 2013). Yet in its 1951 *Econometrica* paper, Richard M. Goodwin explored the non-linear behavior of the business cycle in search of a different explanation for the underlying structure of a given economy. Since then, and even before, several contributions have been proposed for modeling output series taking into account non-linearities.

The Markov-switching autoregressive model of Hamilton (1989) and its extensions, the self-exciting threshold autoregressive model of Beaudry and Koop (1993) and nonlinear error correction models (Escribano, 2004) are examples of specifications aimed at capturing the multifaceted nature of recessions and recoveries. For a more detailed discussion, see Potter (1999), Skalin and Teräsvirta (2002), Teräsvirta (2006). In general, the introduction of nonlinear attributes shall be welcomed given as it contributes to dealing with multiple equilibria, asymmetric adjustments and path-dependent patterns[27].

In this subsection, non-linearities are introduced by means of the multiple-regime smooth-transition autoregressive (MRSTAR) model firstly presented by van Dijk and

[27] It is not surprisingly, then, if one way of exploring hysteresis in unemployment is testing for non-linear dynamics and multiple equilibria in the labour market.

Franses (1999). Two main strengthen point of this approach are the ability of modelling multiple regimes and the attribution of a particular informative content to the transition(s) variable(s). For a univariate time series y_t a general representation of the four-regime MRSTAR model is:

$$\begin{aligned} y_t = &\left\{\phi_1' y_t^{(p)}\left(1 - G_1(s_{1t};\gamma_1,c_1)\right) + \phi_2' y_t^{(p)} G_1(s_{1t};\gamma_1,c_1)\right\} \times [1 - G_2(s_{2t};\gamma_2,c_2)] \\ &+ \left\{\phi_3' y_t^{(p)}\left(1 - G_1(s_{1t};\gamma_1,c_1)\right) + \phi_4' y_t^{(p)} G_1(s_{1t};\gamma_1,c_1)\right\} \\ &\times [G_2(s_{2t};\gamma_2,c_2)] + \varepsilon_t, \end{aligned} \tag{1.41}$$

where $y_t^{(p)} = (1, \tilde{y}_t^{(p)})'$, $\tilde{y}_t^{(p)} = (y_{t-1}, \dots, y_{t-p})'$, $\phi_i = (\phi_{i0}, \phi_{i1,} \dots, \phi_{ip})'$, $i = 1,2,3,4$ and ε_t is a white-noise error process with mean zero and variance σ^2.

The generic transition function $G_j(s_t;\gamma,c)$ with $j = 1,2$ is continuous and bounded between 0 and 1, and, for our purposes, the usual logistic version (LSTAR) is adopted:

$$G_j(s_{jt};\gamma_j,c_j) = \left\{1 + exp\left[-\gamma \prod_{k=1}^{N}(s_{jt} - c_{jk})\right]\right\}^{-1}, \qquad \gamma > 0 \tag{1.42}$$

with γ_j denoting the speed of transition between regimes[28], N the total number of transition points, s_{jt} the transition(s) variable(s) and c_{jk} the threshold(s) value(s) indicating the level of the transition variable at which a transition point occurs.

The main difference between the MRSTAR model here presented and the basic LSTAR version (Granger and Teräsvirta, 1993; van Dijk *et al.*, 2002) is the introduction of two transition functions (instead of one), namely $G_1(s_{1t};\gamma_1,c_1)$ and $G_2(s_{2t};\gamma_2,c_2)$, which enable to consider four distinct regimes. Additional regimes can be directly incorporated by following the same procedure, but this will complicate the notation without modifying the basic insights of the MRSTAR model. At this point, it is interesting to note that the MRSTAR specification nests several other non-linear time series models (van Dijk and Franses, 1999).

[28] Three features of the parameter γ are worth noting: i) $\gamma > 0$ is an identifying restriction; ii) when $\gamma \to 0$ the model in (1.41) 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 $s_t > c$.

The model obtained by combining (1.41) and (1.42) represents, at any given point in time, the evolution of the variable y_t as a weighted average of four different linear autoregressive $AR(p)$ processes. The crucial element of this framework is the choice of the combination of the two transition variables s_{1t} and s_{2t}, which determine the magnitude of the weights associated to each regime. The parameters γ_1 and γ_2 capture the speed at which these weights change when s_{1t} and s_{2t} vary. Each transition variable s_{jt} can be a lagged endogenous variable $(y_{t-d},\ d > 0)$, a linear/nonlinear representation of lagged endogenous variables, a linear trend or an exogenous variable. For a more complete discussion on this, see Teräsvirta (1994).

In their application to US real GNP aggregate data, van Dijk and Franses (1999) use the following two transition variables: for s_{1t} the lagged variation in y_t (Δy_{t-1}), and for s_{2t} a modified version of the current depth of recession measure of Beaudry and Koop (1993)[29]. In doing this, the MRSTAR model is able to describe four different (extreme) regimes: i) expansion with low growth; ii) expansion with accelerating growth; iii) recession with negative growth; iv) recession with positive growth. As a consequence, output evolution is detected according to all the possible complementary scenarios.

The MRSTAR estimation procedure relies upon an extended version of the basic approach proposed by Teräsvirta (1994) for the LSTAR case. More specifically, six steps shall be conducted: a) specifying a linear *AR(p)* model for the dependent variable under analysis; b) testing the null hypothesis of linearity against the alternative of LSTAR; c) if linearity is rejected, defining the appropriate transition function and estimating the LSTAR model; d) testing the null hypothesis of the two-regime LSTAR against the alternative of general MRSTAR by applying the LM test proposed by van Dijk and Franses (1999); e) if the null hypothesis is rejected, estimating the MRSTAR model by conditional maximum likelihood (or nonlinear least squares); e) conducting post estimation robustness checks.

The LM test for discriminating between the presence of two *vs* multiple regimes is constructed along the lines of the test for detecting nonlinearity (Luukkonen *et al.*, 1988), which is based upon a *n*-order Taylor approximation of the underlying process. A similar procedure can be applied to select the optimal number of regimes of the MRSTAR model. Generalized impulse response functions and out-of-sample predictions offer additional

[29] More precisely, the modified current depth of recession (CDR) measure applied is $CDR_t = \max_{z\geq 1}\{x_{t-z}\} - x_t$, with x_t denoting the log of US real GNP.

economic interpretations arising from this model. At this point, one natural question can be advanced: how these models can improve the knowledge of regional recessions and recoveries?

Although this is a quite unexplored topic, two suggestive answers can be proposed. First, some recent contributions (Pedé *et al.*, 2011; Lambert *et al.*, 2012) have addressed the estimation of spatial versions of the LSTAR model, by incorporating spatial interactions in the Taylor-approximation of the transition function. In principle, this can be also valid for MRSTAR extensions. Further research, however, is required. Second, a more intuitive idea can be developed around the link between a national transition variable and regional dynamics. Indeed, the reaction of region-specific series to a variation in a common aggregate variable can shed light on some cross-sectional asymmetries in response to particular phenomena. 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.

Nonlinear approaches to recessions and recoveries represent a quite differentiated spectrum of techniques. Although their structure requires sometimes *ad hoc* estimation procedures, in some cases (especially for unemployment) they provide a good approximation of the true structure of a given economy. The accuracy of non-linear specifications in forecasting is a vivid area of debate among macro econometricians (Teräsvirta, 2006; Ferrara *et al.*, 2013). Two aspects are worth mentioning here. First, as suggested by Stock and Watson (1999), it shall be welcomed the comparisons between several nonlinear models when combining forecasts. Second, the prediction performance of non-linear models needs to take into account both the counterbalancing effect of parameter estimation (Lundbergh and Teräsvirta, 2002) and the choice between iterative and direct forecasts (Lin and Granger, 1994).

V. Conclusion

As other relevant topics in regional economics, in the last two decades the study of regional recessions and recoveries has received many attention at both theoretical and empirical level. In particular, empirical contributions have increasingly represented the bulk of this area of research, with a large part represented by econometric works. Although the appealing of this issue has resulted in a vivid strand of literature, one negative aspect has progressively emerged: the difficulty of disentangling the main results achieved during these years and the lack of clarity in providing a sounded ground for addressing future research.

The main objective of this work has been the identification of a possible synthesis to help understanding where we are and where we shall go in next years for improving our knowledge about regional recessions and recoveries. Moreover, I have tried to motivate why it is important to study the disaggregate effect of crises and upturns at infra national level. Having these purposes in mind, the regional resilience framework recently conceptualized has offered a suitable starting point for broadening the research perspective here applied. Specific theoretical and empirical approaches have been presented in order to design a more unified conceptual framework.

Some concluding remarks are introduced in order to speculate on some possible avenues for future research. In particular, three areas seem worthwhile to be undertaken. First, more theoretical efforts are required for understanding the determinants of shock-propagation at infra national level and the degree of asymmetries in terms of shock-absorption and post-recessionary behaviour across geographical areas. In other words, empirical findings need to be integrated within a more robust theoretical framework.

Second, comparing different econometric perspectives (e.g. linear and nonlinear) can provide a more accurate view on the differentiated effects of national-wide recessions on regional evolution. Further efforts shall be concentrated on the identification of temporary and persistent impacts of recessions. Also, the cointegrated nature of national and regional output series can provide a complementary view for a better understanding of this phenomenon. Contributions focusing on cross-regional comparisons among different countries are also a potential worthwhile task. Finally, forecasting exercises in this area can represent a turning point. Indeed, by simulating and predicting different possible scenarios, they can provide a more sounded basis for claiming place-specific monetary and fiscal countercyclical policies.

References

Artis M., C. Dreger, and K. Kholodilin (2011), What drives regional business cycles? The role of common and spatial components, *The Manchester School*, 79 (5):1035-1044.

Ball L.M. (2009), Hysteresis in unemployment: old and new evidence, *NBER working paper*, n. 14818.

Barca F., P. McCann and A. Rodríguez-Pose (2012), The Case for Regional Development Intervention: Place-Based versus Place-Neutral Approaches, *Journal of Regional Science*, 52(1):134-52.

Beaudry P. and G. Koop (1993), Do recessions permanent change output?, *Journal of Monetary Economics*, 31: 149-163.

Beenstock M. and D. Felsenstein (2007), Spatial vector autoregressions. *Spatial Economic Analysis*, 2(2):167-196.

Belke A. and J.H. Heine (2006), Specialisation patterns and the synchronicity of regional employment cycles in Europe, *International Economics and Economic Policy*, 3:91-104.

Blanchard O.J. and L.H. Summers (1987), Hysteresis in unemployment, *European Economic Review*, 31(1-2): 288-295.

Blien U., S. Fuchs and G. Hirte (2013), New advances in the analysis of regional labour markets, *Papers in Regional Science*, 92(2): 243-248.

Calvo G.A., F. Coricelli and P. Ottonello (2012), The labor market consequences of financial crises with or without inflation: jobless and wageless recoveries, *NBER Working Paper n. 18480*.

Carlino G. and R. DeFina (1998), The differential regional effects of monetary policy, *Review of Economics and Statistics*, 80(4):572-587.

Cerra V., U. Panizza and S.C. Saxena (2013), International evidence on recovery from recessions, *Contemporary Economic Policy*, 31(2): 424-439.

Chauvet M. and J.D. Hamilton (2005), Dating Business Cycle Turning Points, in Van Dijk, Milas, and Rothman (eds), *Nonlinear Time Series Analysis of Business Cycles*; Elsevier's Contributions to Economic Analysis Series*,* 1-54.

Chauvet M., and J. Piger (2008), A Comparison of the Real-Time Performance of Business Cycle Dating Methods, *Journal of Business and Economic Statistics*, 26: 42-49.

Clark T.E. (1998), Employment Fluctuations in U.S. Regions and Industries: The Roles of National, Region-Specific, and Industry-Specific Shocks, *Journal of Labor Economics*, 16(1):202-229.

De Haan J., R. Inklaar, and R. Jong-A-Pin (2008), Will business cycles in the euro area converge? A critical survey of empirical research, *Journal of Economic Surveys*, 22(2):234-273.

Di Giacinto V. (2003), Differential regional effects of monetary policy: a geographical SVAR approach, *International Regional Science Review*, 26(3):313-341.

Di Giacinto V. (2010), On vector autoregressive modeling in space and time, *Journal of Geographical System*, 12:125-154.

Escribano A. (2004), Nonlinear error correction: the case of money demand in the United Kingdom (1878 – 2000), *Macroeconomic Dynamics*, 8: 76 – 116.

Farmer R.E.A. and J.T. Guo (1994), Real Business Cycles and the Animal Spirits Hypothesis, *Journal of Economic Theory*, 63: 42-73.

Farmer R.E.A. (2008), Old Keynesian Economics, in *Macroeconomics in the Small and the Large*, ed. by R.E.A. Farmer, ch. 2, pp. 23-43, Edward Elgar, Cheltenham, UK..

Farmer R.E.A. (2010), How to reduce unemployment: a new policy proposal, *Journal of Monetary Economics: Carnegie Rochester Conference* Issue, 57(5): 557-572.

Farmer R.E.A. (2012), The evolution of endogenous business cycles, *NBER working paper*, n. 18284.

Farmer R.E.A. (2013), Animal spirits, financial crises and persistent unemployment, *The Economic Journal*, 123(568): 317-340.

Fatas A. and I. Mihov (2013), Recoveries, *CEPR Discussion paper*.

Fingleton B., H. Garretsen, and R. Martin (2012), Recessionary shocks and regional employment: Evidence on the resilience of UK regions, *Journal of Regional Science*, 52(1):109-133.

Fingleton B. and S. Palombi (2013), Spatial panel data estimation, counterfactual predictions, and local economic resilience among British towns in the Victorian era, *Regional Science and Urban Economics*, 43:649-660.

Forni M., M. Hallin, M. Lippi and L. Reichlin (2000), The generalized dynamic-factor model: Identification and estimation, *Review of Economics and Statistics*, 82(4):540-554.

Göcke M. (2002), Various concepts of hysteresis applied in economics, *Journal of Economic Surveys*, 16(2):167-188.

Greenaway-McGravy R. and K. Hood (2013), How mobile is labour in the US, *BEA working paper*.

Hamilton J.D. and M.T. Owyang (2012), The propagation of regional recessions, *Review of Economics and Statistics*, 94(4): 935-947.

Harding D. and A.R. Pagan (2002), Dissecting the cycle: a methodological investigation, *Journal of Monetary Economics* 49(2): 365–381.

Justiniano A., G.E. Primiceri and A. Tambalotti (2010), Investment shocks and business cycles, *Journal of Monetary Economics*, 57(2): 132-145.

King R.G., C.I. Plosser and S.T. Rebelo (1988), Production, growth and business cycles: The basic neoclassical model, *Journal of monetary Economics*, 21(2), 195-232.

Kline P. (2010), Place based policies, heterogeneity, and agglomeration, *American Economic Review*, 100(2): 383-387.

Martin R. (2012), Regional economic resilience, hysteresis and recessionary shocks, *Journal of Economic Geography*, 12(1):1-32.

Moretti E. (2011), Local labor markets, *Handbook of Labor Economics*, 4:1237-1313.

Morley J. and J. Piger (2012), The asymmetric business cycle, *The Review of Economics and Statistics*, 94(1): 208-221.

Morley J., J. Piger and P.L. Tien (2012), Reproducing Business Cycle Features: Are Nonlinear Dynamics a Proxy for Multivariate Information?, *Studies in Nonlinear Dynamics & Econometrics.*

Owyang M.T., J. Piger, and H.J. Wall (2005), Business cycle phases in US states, *The Review of Economics and Statistics*, 87(4):604-616.

Owyang M.T., J. Piger and H.J. Wall (2012), Forecasting national recessions using state level data, *Federal Reserve Bank of St. Louis Working Paper*, 2012-013A.

Owyang M.T., D.E. Rapach and H.J. Wall (2009), States and the business cycle, *Journal of Urban Economics*, 65(2):181-194.

Papyrakis E. and R. Gerlagh (2007), Resource abundance and economic growth in the United States, *European Economic Review*, 51(4):1011-1039.

Plotnikov D. (2013), Hysteresis in unemployment and jobless recoveries, *UCLA working paper.*

Potter S.M. (1999), Nonlinear time series modelling: an introduction, *Journal of Economic Surveys*, 13(5): 505 – 528.

Quah D.T. (1996), Aggregate and regional disaggregate fluctuations, *Springer.*

Raurich X., H. Sala and V. Sorolla (2006), Unemployment, growth, and fiscal policy: new insights on the hysteresis hypothesis, *Macroeconomic Dynamics*, 10(3):285-316.

Reggiani A., T. De Graaf and P. Nijkamp (2002), Resilience: an evolutionary approach to spatial economic systems; *Networks and Spatial Economics*, 2(2): 211-229.

Rotemberg J.J. and M. Woodford (1995), Dynamic General Equilibrium Models with Imperfectly Competitive Product Markets, in T.F. Cooley (ed.) *Frontiers of Business Cycle Research*, ch. 9, pp. 243- 293, Princeton University Press, Princeton, NJ.

Skalin J. and T. Teräsvirta (2002), Modeling asymmetries and moving equilibria in unemployment rates. *Macroeconomic Dynamics*, 6(2): 202 – 241.

Smets F. and R. Wouters (2007), Shocks and Frictions in US Business Cycles: A Bayesian approach, *American Economic Review*, 97(3):586-606.

Stadler G.W. (1994), Real business cycles, *Journal of Economic Literature*, 32(4): 1750 – 1783.

Stock J.H. and M.W. Watson (1989), New Indexes of Coincident and Leading Economic Indicators, *NBER Macroeconomics Annual 1988*, 351-394.

Stock J.H. and M.W. Watson (1999), Forecasting inflation, *Journal of Monetary Economics*, 44:293-335.

Stock J.H. and M.W. Watson (2003), Has the Business cycle changed and why?, *NBER Macroeconomics Annual 2002*, 159-230.

Summers L.H. (1986), Some skeptical observations on real business cycle theory, *Real business cycle: a reader*, Routledge.

Teräsvirta T. (1994), Specification, estimation and evaluation of smooth transition autoregressive models, *Journal of the American Statistical Association*, 89: 208 – 218.

van Dijk D. and P.H. Franses (1999), Modeling multiple regimes in the business cycle, *Macroeconomic Dynamics*, 3: 311 – 340.

van Dijk D., T. Teräsvirta and P.H. Franses (2002), Smooth transition autoregressive models – a survey of recent developments, *Econometric Reviews*, 21(1): 1 – 47.

Wall H.J., (2012), The employment cycles of neighboring cities, *Regional science and Urban* Economics, 43(1): 177-185.

Recessions, recoveries and regional resilience:

Evidence on Italy

Abstract

This paper aims to study the effects of employment shocks on the 20 Italian regions (NUTS II) and their recovery capability over the past four decades. The evolution of manufacturing employment at regional level is also presented for integrating the analysis. Transient and permanent effects of employment shocks are described by adopting a quite flexible econometric approach. The resilience of Italian regions is analysed and tested in order to find out possible geographical asymmetries. Spatial interdependency across regions is introduced trough the structure of the error terms and a specific Cholesky decomposition. Selected regional comparisons provide evidence on the territorial unevenness of regional resilience in Italy. Some concluding suggestions introduce possible future areas of research based upon the causes behind regional resilience and the policies which can be adopted.

Keywords: Recessions, recoveries, regional resilience, spatial interdependence.

JEL classification: E32, R11, R15.

I. Introduction

Recessionary shocks and recovery periods have been studied in many disciplines in order to identify origins, analyse consequences and provide policy recommendations. One important question, however, seems to have not been investigated enough in the economic literature: how are booms and busts geographically distributed within a country? Although some recent contributions have studied the geography of crisis and upturns at sub-national level (Wilkerson, 2009; Groot *et al.*, 2011; Hamilton and Owyang, 2012), most of the research in this area still remains spatially-blind.

On the contrary, the spatial unevenness of economic downturns has been evident and clearly observable within nations over the centuries. And the same has been true for post-recessionary stages. While some places show a strong attitude toward shock-absorption, re-orientation of activities and ability to recover; others are less responsive to slumps and deeply affected, remaining in struggle for years. Differences in regional business cycles and asymmetric growth trajectories among diverse cities are tangible examples.

The regional resilience framework recently conceptualized (Martin, 2012) bridges this gap, providing a place-aware synthesis for the study of shocks at territorial level. It allows considering both the temporary impact of exogenous disturbances on a given equilibrium level ('engineering resilience') and the persistence of out-of-equilibrium regional evolutions *à la* Kaldor-Myrdal ('ecological resilience'). Moreover, it represents a different way of analysing the relations between adverse shocks and economic growth in various areas.

Following the econometric specification adopted by Fingleton *et al.* (2012) for the UK case, this paper aims to study the effects of employment shocks on the 20 Italian regions (NUTS II) and their recovery capability over the past four decades. The availability of different series allows to apply this strategy at both aggregate and sector-specific level. In particular, a seemingly unrelated regression (**SUR**) model will be used in order to test the relevance of (engineering) resilience of Italian regional employment to the recessionary shocks in the sample. It is well-known that the SUR model is able to capture simultaneous spatial interdependencies among different units without specifying the familiar spatial matrix (**W**), overcoming some theoretical issues recently observed (Partridge *et al.*, 2012).

Permanent effects and possible time differentiated shocks spillovers across the Italian regions will be analysed using a vector error-correction model (**VECM**) estimated including interregional employment interdependencies. Given the nonstationarity **I(1)** of all the regional employment series the VECM specification favours the articulation of shocks as temporary and persistent. Orthogonalized impulse response functions (**OIRFs**) obtained by a particular Cholesky decomposition will be reported for measuring the effect of a unit shock to one particular endogenous variable at a specific time.

In the past forty years Italy had experienced three main economic crises before the latest depression (Bassanetti *et al.*, 2010): in the early 1970s on the occasion of the Yom Kippur War; in the early 1980s after the Iranian Revolution; in the early 1990s after the depreciation of the Italian *Lira* in September 1992. The present crisis, originated in the US in the second half of 2007 as a financial slump, is still ongoing and, then, interpretations shall be proposed *cum granu salis*.

The analysis hereafter proposed achieves three main objectives. First, it contributes to the growing literature on regional resilience providing original empirical evidences on Italy. Second, it allows to unveil the region-specific effects of the different recessions and recoveries experienced in Italy in the last four decades. Third, it describes the evolution of Italian regions by comparing transient and permanent employment impacts caused by various shocks.

The remaining of the paper is organized as follows. Section II briefly discusses the regional resilience theoretical framework. Section III describes the data and illustrates some preliminary empirics. The econometric analysis is developed in section IV. Section V summarizes and concludes speculating on some possible explanations for differences in resilience across regions over time.

II. Regional resilience

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 place after a recession (Simmie and Martin, 2010; Martin, 2012). The former presents similarities with the well-known 'plucking' model of Milton Friedman and its extensions (Kim and Nelson, 1999); while the latter can be better understood as a hysteretic evolution of a particular economic context showing long-run not-equilibrating trajectories (Redding *et al.*, 2011).

Engineering resilience captures the sensitivity of a region affected by a generic shock and its capability to regain its stable growth pattern. In this sense, it can be described as transient resilience. A particular fluctuation is able to impose a reduction in the level of a variable for a certain period, but its structural trend is re-established in the long run (peak-reversion effect). As a consequence, a decline in GDP or employment does not influence an economy in a perpetual way, given that a place such a region or a city is involved in a self-equilibrating continuous process.

More resilient regions are expected to suffer less in terms of magnitude and recover faster than less resilient regions. Hence, differences in cumulative losses occurred during recessions and post-recessionary positive changes result helpful in order to detect engineering resilience. Historical asymmetries in the shock-absorption showed by different places have been traditionally observed at both regional (Owyang *et al.*, 2009; Artis *et al.*, 2011) and urban (Glaeser *et al.*, 2011) level.

The recent adoption of Markov-switching techniques in the regional business cycles literature (Owyang *et al.*, 2005) offers a possible alternative way of assessing engineering resilience: regional differences in the timing of a recessions ('entry' and 'exit') can be conceived as a signal of transient resilience. Hence, regions affected longer than the national average, with anticipated entry and postponed exit, may be candidates to be less resilient than the rest of the nation.

At the other end of the spectrum, the notion of ecological resilience denotes a situation where the adverse effects of crises become permanent not dying out over the periods. This view of resilience is closed to the rooted concept of hysteresis in Economics, which highlights the persistence of specific disturbances influencing the path of an economy. A given area, then, does not necessarily evolve through self-adjusting dynamics, but it can experience multiple patterns such as non-ideal relay (Göcke, 2002) and memory of recessions (Cross *et al.*, 2010).

As extensively discussed in Martin (2012), a particular shock can shift downward/upward the long-run potential of a system while maintaining a constant rate of variation or, alternatively, it is able to cause both a change in the structural evolution of a system and a negative/positive long-run growth. Whether a depressing case can be associated to a perverse cumulative dynamic, a more optimistic one arises from a process of creative destruction *à la* Schumpeter where the turning point is represented by the adverse shock.

Studying ecological resilience, therefore, represents an alternative way of analysing the impact of crises on the growth paths experienced by different geographical areas. In this sense, regional resilience can be thought as a complementary step for a better understanding of regional evolutions. Moreover, it contributes to integrate some recent empirical works relating economic and political crises to economic growth in cross-country comparisons (Cerra and Saxena, 2008; Panizza *et al.*, 2009).

Although the regional resilience framework is *in fieri* both in theory and in practice, it provides a unified perspective for investigating the various explanations traditionally proposed in order to justify the geographical unevenness of recessions and recoveries within and across countries. Similar productive contexts, for instance, will probably experience symmetric rises and falls (Clark and Van Wincoop, 2001; Kalemli-Ozcan *et al.*, 2001). Regions may become more synchronized in reacting to shocks *ex post* the institution of a common market (Barrios and Lucio, 2003), depending on the distribution of human capital (De Haan *et al.*, 2008) or according to a particular product fragmentation across territories (Ng, 2010).

The permanent effects of crises observed in given areas have been ascribed to the one-way migration of people and ideas (Martin and Sunley, 1998) and to the permanent relation between employment growth and attractiveness to outside labourers across territories (Burridge and Gordon, 1981). On the contrary, the presence of small and innovative firms can facilitate the recovery phase, benefiting from flexible structures and risk-taking behaviour (Clark *et al.*, 2010), as well as the reallocation of productivity through cleansing effects which is able to re-address a given system towards productive-enhancing activities (Caballero and Hammour, 1994).

Considering simultaneously engineering and ecological resilience means analysing a particular economic context in two alternative scenarios: in-balance and out-of-balance. Although modelling shock-absorption and shock-persistence across regions taking into account spillovers effects is not a trouble-free task, unveiling the spatial distribution of benefits and losses deriving from recessions and recoveries can contribute to the debate concerning regional development. The next pages will deal with this task for the Italian case.

III. Italian regional evolution: preliminary empirics

The empirical part is based on Italian regional data for employment over the period 1977-2011. Employment series have been preferred to GDP or other economic measures for two main reasons: first, they are more articulated at regional level and need not be deflated; second, they provide interesting insights on the evolution of a regional context (Blanchard and Katz, 1992), though they can be affected by issues related to place-specific frictions in labour markets.

Annual series are available for the whole period, while quarterly data range from 1992(IV) to 2012(I)[1]. More precisely, then, we have two distinct series for the 20 Italian regions (NUTS II): annual data (t=35) and quarterly data (t=78). This difference is mainly due to changes in the methodology of collection adopted by the Italian National Institute of Statistics during these years (ISTAT, 2004). In particular, quarterly data for employment collected *ante* 1992 are not comparable with the series elaborated *post* 1992.

Insert about here:
Figure 1.a,b. – Italy employment level (Millions) and growth rate, 1977-2011.

Figure 1 illustrates aggregate Italian employment both in level and growth rate for annual data. The sample period contains three main national adverse shocks: the early 1980s, the *Lira* crisis in the early 1990s and the last recession started in 2008.

The first crisis was experienced in the early 1980s and it was part of a extended slowdown in the economic activity registered in Italy and in other European countries over all the Seventies. It caused a substantive reduction in output, exports and internal consumption, while employment was less affected (Bassanetti *et al.*, 2010). Perhaps the mild shifting in occupation can be justified with the massive utilisation of generous temporary work subsidies and the increased public labour demand arising from the contextual process of regional administrative decentralization started in the second half of the Seventies.

Comparisons of employment at regional level are difficult to be made over the 1970s, given that the regional series elaborated by ISTAT only starts in 1977. However, using a complementary dataset provided by the research centre CRENOS some interpretations on the geographical distribution of the two main recessions in the 1970s-1980s can be advanced.

In particular, some regions such as Piedmont, Liguria, Friuli V.G. and Sardinia were more affected than the overall country, showing longer negative dynamics than the national one. By contrast, other regional contexts registered lower decline in the total number of

[1] In what follows, the main sources of data are ISTAT (Italian National Institute of Statistic) and CRENOS (Centre for Economic Research North-South). A complementary series ranging from 1970 to 2009 will be used to integrate the discussion on the recessionary events occurred in the Seventies. This additional dataset, elaborated by CRENOS, has been created from Italian regional accounts and other related sources (Paci and Saba, 1998).

occupied than the national average as in the case of Veneto, Lombardia, Emilia-Romagna, Toscana, Lazio and Campania[2].

The recovery phase registered in the second half of the 1980s was characterized by the emergence of a common positive trend in employment shared by the regions in the Centre-North and being part of the well-known 'Third-Italy'. Other favourable exceptions were Campania and Sardinia. The post-recessionary cumulative growth showed by other regions, mainly most of the Southern areas and the traditional industrial ones, was lower than the Italian aggregate.

Insert about here:
Figure 2. – Italy employment growth rate, 1992(IV)-2012(I).

Figure 2 above shows the Italian employment growth from 1992(IV) to 2012(I). It is clearly observable why, before the latest recession started in 2008, the *Lira* crisis was identified as the Italian 'Great Recession' with relevant employment losses from late 1992 to the beginning of 1995. For instance, in 1993, Miniaci and Weber (1999) reported a decline in GDP of around 1.2% and household disposable income falling by 5%.

The announcement of devaluating the Italian *Lira* operated by the government in September 1992 is generally recognized as the starting point of the Italian currency crisis. This prolonged slumps, officially ended after six quarters in 1995(I), caused almost one third of cumulative loss in terms of external value and sudden depreciation in the real exchange rate: a fall by 10.25% was registered only over the last quarter of 1992. Moreover, it contributed to temporarily pushing Italy out of the European Monetary System.

Whether the consequences on inflation were less strong than expected, due to some structural reforms launched in late-1980s, interest rates substantially raised creating relevant problems for the equilibrium of the public sector. In addition, the Italian labour market experienced a substantive fall in employment (more than 4% summing over the six quarters), deepened by the prior reform of temporary layoff schemes introduced in 1991 on the basis of more restrictive criteria.

A diachronic comparison with the recent recession results difficult for two evident reasons. First, even if the official timing range from 2008(II) to 2010(III) it is clear that the last crisis is not completely over. Second, the concomitant presence of 'three crises'

[2] The qualitative analysis for the 1970s-1980s is deliberately incomplete for two reasons. First, difficulties related to affordable time series for regional employment, given the different techniques adopted by ISTAT. Second, given the limited availability of quarterly data, the focus will be on the two more recent crises.

(financial, Euro and sovereign debt) characterizing the present recession requires cautious explanations. Limiting the observation to the reduction of aggregate employment registered between late 2008 and the end of 2010, Italy had experienced more than 2% of employment losses.

As discussed in Martin (2012) and Fingleton *et al.* (2012), regional resilience can be better described by using some particular indexes. Table 1 reports the sensitivity of the 20 Italian regions to the two most recent recessionary shocks, calculated as the regional percentage decline in employment relative to the national decline during each adverse event.

Insert about here:
Table 1. – Italian sensitivity index.

During the *Lira* crisis some regions were more resistant than the national counterpart (sensitivity index lower than 1), while others, mainly in the Centre-South, suffered high cumulative losses in employment with respect to Italy as a whole. This strong polarization was probably caused by both the contemporaneous abolition of the specific additional measures devoted to the Italian *Mezzogiorno* (i.e. extra-ordinary regional programs) and the increased flexibility introduced in public employment, highly diffused in these areas.

A more complex situation seems to appear across the Peninsula when considering the regional differences in sensitivity originated from the current economic slump. Despite these observations must be cautiously interpreted, it emerges the absence of a clear spatial divide. Disaggregating this index at sector level it can be noted the higher sensitivity of some industries such as building, petrochemicals, mechanical and retailing. These results are confirmed for both recessionary events heretofore discussed.

Insert about here:
Table 2. – Italian recovery index.

Table 2 contains the recovery index of Italian regions for the period between the two more recent crises (1995(II) – 2008(I)), defined as the post-recession percentage growth in employment in a region relative to the percentage growth in national employment. In the aftermath of the *Lira* crisis the relative employment growth followed the rooted North-South divide, with higher reactions registered in the Central and Northern regions and most of the Southern areas remaining below the Italian average. Similar trends have been found in a different study focused on the identification of co-movements in regional business cycles in Italy (Mastromarco and Woitek, 2007).

It is worth mentioning, however, the presence of relevant differences in magnitude across Italian regions. In the North, for instance, the recovery of Piemonte and Liguria was lower than most of the other regions in the same area and the Italian average. By comparison, Abruzzo, Sardegna and Sicilia registered the highest post-recessionary performances among the regions in the Centre-South.

Figure 3 below compares the sensitivity of Italian regions to the *Lira* crisis and their recovery performance up to the recent recession. Low resilient regions (high sensitive) seem to bounce back (low recovery) less than more resilient regions.

Insert about here:
Figure 3. – Italian sensitivity and recovery.

Considering the *Lira* crisis and the subsequent post-recessionary period the 20 Italian regions seem to have followed three possible patterns: high resistance and high recovery (most of the regions in the Centre-North); medium resistance and low recovery (Piemonte, Liguria and Sardinia); low resistance and low recovery (most of the Southern regions excluded Abruzzo). A peculiar trajectory was experienced in Lazio, the region of Rome, with high sensitivity and high recovery capability.

IV. Econometric analysis

IV.1 Transient resilience

Engineering resilience can be captured by estimating the coefficients of both recessions and recoveries at regional level and testing the possible heterogeneity across regions. Following Fingleton *et al.* (2012), in the presence of contemporaneous correlation between units seemingly unrelated given different parameters, i.e. regions in our case, a SUR model can be useful to describe possible underlying relations via the correlation of the error terms, without introducing prior assumptions on the spatial interdependence.

A general representation of the SUR model can be written as:

$$y_{it} = \alpha_i + x'_{it}\gamma_i + \varepsilon_{it} \tag{2.1}$$

$$E[\varepsilon_{it}\varepsilon_{jt}] = \sigma_{ij};\ E[\varepsilon_{it}\varepsilon_{js}] = 0\ (\forall i, j\ and\ t \neq s) \tag{2.2}$$

where y_{it} is the dependent variable observed at n time moments (t =1,….,n) for a number m of units (i =1,….,m), α_i is the unit specific coefficient, x_{it} is the set of explanatory variables for unit i at time t, γ_i is the coefficient of the explanatory variables and ε_{it} is the error term.

The assumption that the disturbances of each unit are not serially correlated is maintained, while the mn x mn covariance matrix **Ω** is not of the form $\boldsymbol{\sigma^2 I}$ having the following structure:

$$\begin{pmatrix} \sigma_{11}\boldsymbol{I} & \sigma_{12}\boldsymbol{I} & \cdots & \sigma_{1m}\boldsymbol{I} \\ \sigma_{12}\boldsymbol{I} & \sigma_{22}\boldsymbol{I} & \cdots & \sigma_{2m}\boldsymbol{I} \\ \vdots & \vdots & & \vdots \\ \sigma_{1m}\boldsymbol{I} & \sigma_{2m}\boldsymbol{I} & \ldots & \sigma_{mm}\boldsymbol{I} \end{pmatrix}$$

In this case, the estimation procedure is based upon the *generalized least squares* (**GLS**) estimator, more efficient than the *ordinary least squares* (**OLS**)[3]. Moreover, a prerequisite for applying the SUR model is that the number of units m shall not be larger than the number of time series observations n per unit, because a non-singular estimator of **Ω** is required.

For the annual series ranging from 1977 to 2011, the following SUR model has been estimated in order to describe regional employment growth as determined by: i) region-specific growth rate; ii) recessionary events; and iii) post-recessionary periods:

$$\Delta emp_{it} = \beta_{0i} + \beta_{1i}Rec_{1t} + \beta_{2i}Rec_{2t} + \beta_{3i}Rec_{3t} + \beta_{4i}Post_{1t} + \beta_{5i}Post_{2t} + \varepsilon_{it} \tag{2.3}$$

[3] In reality, the covariance matrix **Ω** is unknown and the estimation procedure involves the adoption of a feasible *generalized least squares* (**FGLS**) estimator obtained through iterative procedures. In two particular cases, however, the **GLS** estimator in the SUR model corresponds to applying the OLS estimator per unit: i) different units are uncorrelated (σ^2_{ig}= 0); ii) all units have the same regressor matrix ($\boldsymbol{X_i}$=$\boldsymbol{X}$ is the same for all i =1,….,m).

where:

Δemp_{it} = employment growth in region i (i =1,….., 20) at year t (t =1978,….., 2011);

β_{0i} = region-specific (autonomous) growth rate;

β_{1i}, β_{2i}, β_{3i} = change in employment growth rate as recession dummies: Rec_{1t} (1982-1984); Rec_{2t} (1992-1995); Rec_{3t} (2008-2010);

β_{4i}, β_{5i}, change in employment growth rate during post-recession periods: $Post_{1t}$ (1985-1991); $Post_{2t}$ (1996-2007);

ε_{it} = error terms with $E[\varepsilon_{it}\,\varepsilon_{it}] = \sigma^2_{ii}$ and $E[\varepsilon_{it}\,\varepsilon_{jt}] = \sigma^2_{ij}$.

The dating of the recessionary events is exogenously defined for the whole nation on the basis of our datasets and according to the official analyses elaborated by the Bank of Italy and the Italian Institute for Studies and Economic Analyses (ISAE)[4]. Hence, we have adopted the exogenous approach (Harding and Pagan, 2003) rather than the endogenous one (Hamilton, 2003). Regarding the particular structure of the errors, temporal homoscedasticity has been previously tested applying the well-known Likelihood-Ratio Test, rejecting the presence of heteroscedasticity.

Estimation results and graphs for all regions are reported in the Appendix. It is plain that the main purpose of this model is to describe the influence of particular moments, recessions and recoveries, on the evolution of Italian regional employment rather than finding out explanations behind the employment growth itself.

The (unrestricted) SUR model in (2.3) represents a starting point for testing various hypotheses able to identify the spatial patterns of engineering resilience across Italian regions. In particular, in line with Fingleton *et al.* (2012) the following restrictions have been tested:

a) $\beta_{1i} = \beta_{2i} = \beta_{3i}$: for each region the impact of recessions is constant over time;
b) $\beta_{r1} = \beta_{r2} = \beta_{r3} = \beta_{r4} = \beta_{r5} = ...$: the impact of each recession (r = 1,2,3) is the same for all regions;

[4] In contrast with the US where the official dating of economic crises is provided by the National Bureau of Economic Research, a conventional timing of recessionary events is not present for the Italian case. Nevertheless, it has been followed the timing adopted by two of the main national economic institutions and confirmed by the historical knowledge.

c) $\beta_{4i} = \beta_{5i}$: for each region the impact of postrecession recovery is constant across time;

d) $\beta_{s1} = \beta_{s2} = \beta_{s3} = \beta_{s4} = \beta_{s5} = ...$: the impact of each postrecession (s = 1,2) is the same for all regions.

Whereas restrictions (a) and (c) contribute to explain possible differentiated effects of both recessions and recoveries introduced in the estimation, testing (b) and (d) means investigating the presence of geographical asymmetry in the shock-absorption and in the recovery phase of Italian regions. For each recession and postrecession the null hypothesis of geographical evenness (same impact for all regions) can be rejected at all levels of significance.

Insert about here:
Figure 4. – Selected regional comparisons SUR annual.

Selected regional comparisons based on the fitted values of the model in (2.3) can suggest some interpretations about the evolution of regional resilience in Italy in the last four decades. Graphs reported in figure 4 show four relations among some representative regions. Even if we are not interested in the way the fitted values are able to model regional employment evolution according to the specified model, the presentation of these comparisons allows to analyse the asymmetric behaviour of different regions in response to a given shock.

Piemonte and Veneto are both located in the North of Italy: the former denotes an old industrial area which has experienced in recent years a relevant structural process for redefining its activities, while the latter is part of the 'Third-Italy' and relies upon a dynamic set of small and medium enterprises. Similar arguments can be extended to the pair 'Liguria – Marche', with the only exception that Marche is located in the Centre of Italy.

The selection of the other two couples of regions, namely 'Emilia Romagna – Campania' and 'Toscana – Puglia', has been oriented by the aim of showing differences in the employment evolution between two areas in the Centre-North (Emilia Romagna and Toscana) and two in the South (Campania and Puglia) having similar total population. Moreover, Campania and Puglia have traditionally shared the presence of rooted industrial districts in line with the structure of other regions such as Emilia Romagna and Toscana.

For each pair of regions two evident aspects are worth mentioning. First, regional heterogeneity during recessions and postrecessions can be observed by the different magnitude of the estimated coefficients. In the first case (Piemonte *vs* Veneto), for instance, this pattern emerges with clarity: employment growth in Piemonte always registers lower levels than Veneto. Second, it shall be recognized the variation across time of both adverse shocks and recovery periods: these events show a time variant evolution.

Comparing Piemonte and Veneto it can be noted the lower resilience of the former, a traditional industrial region, during all negative shocks and their aftermaths. In the second case, Liguria *vs* Marche, changes in employment growth are more varied, with Liguria suffering more than Marche in the first crisis and in the last one, but performing better both in the first postrecession period and during the downturn of the early-1990s.

Despite the presence of differences in magnitude, the two North-South comparisons (Emilia Romagna *vs* Campania and Toscana *vs* Puglia) are characterized by a common pattern: all the regions in the South were more resistant to the negative shock of the Eighties, results also confirmed for the Seventies using the auxiliary dataset, but their sensitivity increased in the subsequent two crisis.

This variation in the absorptive capacity of Southern regions could be ascribed to the relative reduction of the share of public employment experienced in the South in the early-1990s. In the same direction, it is interesting to note the contemporaneous introduction of more flexible contracts in the public sector (the so-called 'privatization of public jobs' started in 1992) which had a major impact in those regions having a large number of public workers.

Being a flexible specification, the SUR model has been adopted for describing the evolution of regional employment at sector level and, more precisely, for analysing the resilience of the industrial sector (excluding building). This choice has been motivated for two reasons: first, the sensitive attitude of the industrial sector has been widely recognized by the literature on business cycles; second, negative shocks present in the national industrial series are closer to the aggregate employment fluctuations, than those in the other sectors such as agriculture, building or services[5].

However, interpretations based upon industrial employment need to be addressed with cautions. Indeed, the aggregate analysis here presented does not discriminate between differences in the industrial employment among regions. Either the presence of small and

[5] In this case, employment series are those of the auxiliary dataset elaborated by CRENOS (see footnote n.1).

medium enterprises or the importance of large plants influence the way different regions react to shocks. With this in mind, the following investigation is mostly focused on detecting the aggregate evolution of industrial employment, recognizing some necessary imperfections.

Observations for industrial employment are available for the period from 1970 to 2010. The same specification in (1) has been estimated, using five sector specific recession dummies, namely: i) 1975-1976; ii) 1981-1987; iii) 1991-1993; iv) 1996-1997; v) 2008-2009. The four periods between these recessions (1977-1980; 1988-1990; 1994-1995; 1998-2007) have been used as the recovery variables of the estimation. For industrial employment, the unrestricted model has been tested as follows:

a) $\beta_{1i} = \beta_{2i} = \beta_{3i} = \beta_{4i} = \beta_{5i}$: for each region the impact of recessions is constant over time;
b) $\beta_{r1} = \beta_{r2} = \beta_{r3} = \beta_{r4} = \beta_{r5} =$...: the impact of each recession (r = 1,2,3) is the same for all regions;
c) $\beta_{6i} = \beta_{7i} = \beta_{8i} = \beta_{9i}$: for each region the impact of postrecession recovery is constant across time;
d) $\beta_{s1} = \beta_{s2} = \beta_{s3} = \beta_{s4} = \beta_{s5} =$...: the impact of each postrecession (s = 1,2) is the same for all regions.

Insert about here:
Figure 5. – Selected regional comparisons SUR industry annual.

Figure 5 illustrates the fitted values (restricted SUR) of industrial employment growth for the six pairs of regions yet mentioned. Again, differences in regional resilience (i.e. magnitude of shocks and recoveries) and over time are evident.

Apart from the post *Lira* crisis, Piemonte confirms higher sensitivity and lower recovery than Veneto. Concerning this sector specific employment evolution, Marche performs better than Liguria over the whole time period. More articulated results emerge from the other four relations. All the regions in the North seem to perform better in the aftermath of the *Lira* crisis, perhaps due to their higher export propensity and the contemporaneous increased stimulus of Italian products at international level.

For quarterly data ranging from 1992(IV)-2012(I) the following SUR model has been estimated:

$$\Delta emp_{it} = \beta_{0i} + \beta_{1i} Rec_{1t} + \beta_{2i} Rec_{2t} + \beta_{3i} Post_{1t} + \varepsilon_{it} \qquad (2.4)$$

where:

Δemp_{it} = employment growth in region i (i =1,….., 20) at quarter t (t =1993(I),…..2012(I));

β_{0i} = region-specific (autonomous) growth rate;

$\beta_{1i} = \beta_{2i}$ = change in employment growth rate as recession dummies: Rec_{1t} (1993(I)-1995(II); Rec_{2t} (2008(II)-2010(III));

β_{3i} = change in employment growth rate during alternative post-recession specifications;

ε_{it} = error terms with $E[\varepsilon_{it}\,\varepsilon_{it}] = \sigma^2_{ii}$ and $E[\varepsilon_{it}\,\varepsilon_{jt}] = \sigma^2_{ij}$.

In this case, the recovery dummy $Post_{1t}$ has been defined both following the procedure heretofore adopted (1995(II)-2008(I)) and using different time selection criteria such as: one/two years after a recessionary event; number of quarters from the recessionary event to the first technical recession calculated as two consecutive quarters with negative change.

The unrestricted model in (2.4) has been tested as follows:

a) $\beta_{1i} = \beta_{2i}$: for each region the impact of the two recessions is similar;
b) $\beta_{r1} = \beta_{r2} = \beta_{r3} = \beta_{r4} = \beta_{r5} =$...: the impact of each recession (r = 1,2) is the same for all regions;
c) $\beta_{s1} = \beta_{s2} = \beta_{s3} = \beta_{s4} = \beta_{s5} =$...: the impact of the unique postrecession (s = 1) is the same for all regions.

As a result, a restricted SUR has been performed imposing a common national shock (β_2) for the last recession started in the second quarter of 2008. Estimation results and graphs for all the regions are in the Appendix. Figure 6 shows the fitted values of the six regional comparisons yet discussed, with the postrecession period defined as one year after the first recession (1995(II)-1996(II)).

Insert about here:
Figure 6. – Selected regional comparisons SUR quarterly.

Most of the results previously discussed for the annual series are confirmed. Regional and time specific evolutions continue to occur. Piemonte is more sensitive than Veneto during both recessions in the sample period, but it experienced a higher recovery in the first year after the *Lira* crisis. Liguria seems to perform worse than Marche during and just after the *Lira* crisis. The additional four pairs of regions support, with differences in magnitude, the North-South divide: regions in the North seem to be more engineering resilient than those in the South.

Again, the SUR model has been applied for describing the evolution of industrial regional employment (excluding building). In this case, data availability is limited including observations from 1992(IV) to 2010(IV). Two sector specific recessionary events have been chosen, namely: 1992(IV)-1995(I) and 2008(IV)-2010(II). For the identification of the recovery phase, the same strategy adopted for total employment has been used: i) one/two years after a recessionary event; ii) number of quarters from the recessionary event to the first technical recession; iii) quarters between the first and the second recession.

The unrestricted model for industrial data has been tested applying the same methodology used for aggregate employment (a-c). As a result, a restricted SUR has been estimated imposing a common national impact for the second recession in the sample. Regional comparisons are illustrated in figure 7.

Insert about here:
Figure 7. – Selected regional comparisons SUR quarterly.

As in the previous cases, regional and time variant patterns clearly emerge. Concerning the evolution of industrial employment, Veneto confirms its higher resilience than Piemonte. The same is true for Marche in comparison with Liguria, even if the latter presents a specific dynamic during the *Lira* crisis. The two Southern regions (Campania, and Puglia) seem to have suffered relevant employment losses one year after the *Lira* crisis with respect to their counterparts.

Finally, observing the matrix of the residuals for each estimated model two comments are worth nothing. First, most of the Italian regions confirm the importance of spatial proximity: cross-correlation across regions and distance among them are inversely related. Second, some regions seem to be influenced, in terms of magnitude of cross-correlation, by sectorial similarities: regions with analogous industrial structure (e.g. Lazio and Campania)[6] show more relevant connections than those having different economic systems.

IV.2 Permanent resilience

One possible way of analysing the hysteretic effects caused by one time regional employment shock is the Vector Error-Correction Model fitted to the levels of employment. 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. If y_t is a vector of economic variables that is not in equilibrium in some time periods (i.e. the long-run linear constraint $\alpha' y_t = 0$ does not hold), it can be interesting to model the following equilibrium error:

$$z_t = \alpha' y_t$$

in order to capture the error-correcting mechanism on which a given economy is based upon.

If the vector y_t includes more than two variables the system can be written in the usual Vector Error Correction (VEC) form as follows. Using matrix notation, the starting point is the autoregressive $AR(p)$ representation

$$Y_t = \mathbf{\Pi}_1 Y_{t-1} + \mathbf{\Pi}_2 Y_{t-2} + \cdots + \mathbf{\Pi}_\mathrm{p} Y_{t-p} + \mathbf{\Phi} X_t + \varepsilon_t, \qquad t = 1, \dots, T. \tag{2.5}$$

with $\mathbf{\Pi}_\mathrm{i}$ and $\mathbf{\Phi}$ denoting conformable matrices of coefficients and X_t being a $q \; x \; 1$ vector of deterministic variables (including a constant, trend and dummy variables).

We can rewrite the relation in (2.5) in the error correction form

$$\Delta Y_t = \sum_{i=1}^{p-1} \mathbf{\Gamma}_i \Delta Y_{t-i} + \mathbf{\Pi} Y_{t-1} + \mathbf{\Phi} X_t + \varepsilon_t \tag{2.6}$$

[6] The similarity between Campania and Lazio has been suggested by comparing employment specialization coefficients for the aggregate industry, services and public administration.

where the matrices $\mathbf{\Pi} = \sum_{i=1}^{p} \mathbf{\Pi}_i - \mathbf{I}$ and $\mathbf{\Gamma}_i = -\sum_{j=i+1}^{p} \mathbf{\Pi}_j$ are each $n \ x \ n$, and represent the long-run and the short-run impact matrices, respectively.

If the rank of the matrix $\mathbf{\Pi}$ that premultiplies the levels variables is $r < n$, it is possible to decompose $\mathbf{\Pi}$ as the product of two ($n \ x \ r$) matrices $\boldsymbol{\alpha\beta}'$ with $rank(\boldsymbol{\alpha})$ = $rank(\boldsymbol{\beta})$ = r. As extensively discussed in Johansen (1988), the r columns of $\boldsymbol{\beta}'$ represent the cointegrating vectors and $\boldsymbol{\alpha}$ denotes the loading matrix. In addition, it is important to recognize that the factorization $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$ is not unique since for any $r \ x \ r$ nonsingular matrix $\mathbf{H}$ we have

$$\boldsymbol{\alpha\beta}' = \boldsymbol{\alpha}\mathbf{H}\mathbf{H}^{-1}\boldsymbol{\beta}' = (\mathbf{aH})\left(\boldsymbol{\beta}\mathbf{H}^{-1'}\right)' = \mathbf{a}^{*}\boldsymbol{\beta}^{*\prime},$$

and, as a consequence, the model requires further restrictions (in general, it is adopted a specific normalization procedure) for obtaining unique values of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}'$.

The cointegrating relationships have a structural interpretation: they represent the steady-state of long-run relations characterized by a 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[7]. In other words, the idea of linear cointegration identifies the magnitude of the disequilibrium error from one period that is corrected in the next one. Moreover, with nonstationary series I(1), as in the case of regional employment, and in presence of cointegrated variables this particular specification allows to distinguish between temporary and permanent effects of a given shock.

A parsimonious econometric strategy requires to precisely define the presence of unit root in the series, the number of lags in the vector error correction representation and the number of cointegrating vectors. In our case, the stationarity of employment series has been verified using the traditional Augmented Dickey Fuller (ADF) test. The optimal lag length of the model has been chosen comparing different selection criteria: Akaike information criterion (AIC), Schwarz Bayesian information criterion (SBIC) and Likelihood Ratio (LR) test. The number of cointegration relations has been identified by adopting the well-known Johansen trace test[8].

[7] For a more detailed discussion on the equilibrium implications of cointegration see Beyer and Farmer (2007) and Morley (2007).

[8] The test results are not reported here but available upon request. For a different approach regarding the cointegrating relationships of Italian regions see Cellini and Scorcu (1997).

For quarterly data a VECM with one lag and nine cointegrating relationships has been estimated for a subsample of 17 Italian regions: excluding the three smallest regions, namely Valle d'Aosta, Molise and Basilicata. The test on the eigenvalue stability condition supports the cointegrating relationships adopted, finding out 8 unit moduli, obtained as difference between the number of variables (k =17) and the number of cointegrating relations (r =9)[9].

As discussed in Fingleton *et al.* (2012), the VECM specification allows to separate transient and permanent effects, addressing the initial question on the geographical unevenness of employment shocks across regions in the long-run: the main question is whether shocks tend to zero or they show an hysteretic path. Moreover, this approach favours the investigation of particular causal relations among regions by the adoption of a given spatial order (i.e. a specific Cholesky decomposition).

In contrast with the UK case where the presence of a dominant region (i.e. South East) can be justified on the basis of several arguments, the propagation of shocks across Italian regions follows a more varied pattern and, then, it needs to be studied adopting a more general perspective. As a consequence, the ecological resilience and the sensitivity of Italian regions to shocks is hereafter described using orthogonalized mean responses derived from impulses emanating by all the region in our sample, which can be understood like an Italian average effect in terms of employment.

Orthogonalized impulse response functions

The OIRFs are able to provide one possible (not unique) causal interpretation to our system, even in presence of correlation between disturbances[10]. In our case, the orthogonalization has been obtained imposing a recursive structure on the contemporary relationships of the variables, namely investigating a particular Cholesky decomposition able to identify the scheme of the instantaneous correlations. More precisely, the following order of the variance-covariance matrix has been explored: from the North to the South, responses tend to weaken with distance, being strongest within regions and in

9 Estimation results, the Lagrange-Multiplier test for residual autocorrelations and the traditional tests for errors normality (Jarque-Bera, skewness and kurtosis) are available upon request.

10 Orthogonalized impulse response functions are able to capture the relation between the shock occurred in one variable and the responses of other variables, by imposing a given structure of the variance-covariance matrix.

neighbouring regions[11]. Table 3 reports the mean OIRFs over periods 1-20, given that the specific Cholesky ordering presents nonzero differences in initial responses across regions.

Insert about here:
Table 3. – Mean Responses to Shocks from All Regions.

From the observation of the mean responses of Italian regions, the presence of differences in magnitude is quite evident. Liguria and almost all the Southern regions confirm their high sensitivity when considering shocks regardless of origin. By contrast, most of the regions in the Centre and in the North seem to be, on average, less affected and, then, more resilient regarding employment shocks. The positive responses registered in Veneto and Trentino A.A. might be probably ascribed to the specific dynamics experienced in these regions during the period of observation.

Insert about here:
Figure 8 (a-e). – Mean Responses to Shocks from All Regions.

Figures 8 (a-e) illustrate the mean responses over time in five different macro areas: North-West, North-East, Centre-North, Centre-South and South. For our purposes, two aspects are worth mentioning. First, employment shocks regardless of origin affect each area in a peculiar way in terms of both magnitude and dynamics. Similar trajectories, however, can be observed between the North-West and the Centre-North and between the Centre-South and the South.

Second, region-specific evolutions seem to be also confirmed in the long-run. In the North-West, for instance, a one unit negative shock has a deeper effect, on average, on Liguria rather than on the other regions. In the North-East area, Veneto, Trentino A.A. and Friuli V.G. show fairly different responses, probably due to their diverse economic structures. For instance, traditional industries such as the shipyards present in Friuli V.G. are less responsive to employment shocks than tourism activities spread in Trentino A.A.

Regions in the Centre-North share a common dynamic, though in presence of differences in sensitivity. A similar description can be extended to the Centre-South without taking into account the peculiarity of Abruzzo. Mean responses registered in the

[11] In concrete, the following Cholesky ordering has been applied: Piemonte, Liguria, Lombardia, Veneto, Trentino A.A., Friuli V.G., Emilia Romagna, Toscana, Umbria, Marche, Abruzzo, Lazio, Campania, Puglia, Calabria, Sicilia, Sardegna.

South of Italy confirm the high sensitivity of this macro area with the partial exception of Sardegna.

All the results discussed in this paragraph such as graphs and OIRFs are conditional on the specific model that has been applied and on the particular Cholesky decomposition used (see, footnote 10). In other words, our results rely upon the particular propagation of the shocks that has been adopted and, then, alternative specifications will probably differ. Moreover, it is important to remember the main perspective of this work, a descriptive one, which is not focused on the causes behind the regional variety in long-term resilience. For this reason, our specification is deliberately limited not including additional explanatory variables.

However, the quite simple econometric technique adopted in this paragraph introduces two novel arguments in the debate on regional evolution. First, employment shocks are not only temporary accidents, but they represent structural moments for a given area, being able to originate hysteretic effects. Therefore, the difference between engineering and ecological resilience seems to be plausible. Second, geography matters when considering both recessions and recoveries, given that employment shocks are characterized by region-specific effects. The mosaic of responses observed in the Italian case supports this argument.

V. Conclusion

Some years ago, Barry Eichengreen discussing the link between Macroeconomics and regional issues sustained the importance 'to think harder than we traditionally have' when applying a particular economic analysis to a given area. The regional resilience framework recently theorized goes in this direction, providing a spatially-aware unified perspective for studying regional economic evolution. Using a flexible econometric approach, this paper has investigated this idea focusing on recessions and recoveries experienced in Italy in the last four decades.

Transient (engineering) and permanent (ecological) resilience has been observed across Italian regions, confirming the presence of a process which is characterized by its geographically unevenness. From our analysis, past and recent employment dynamics in Italy are far from being a homogeneous picture, with region-specific differences quite recognizable in the shock-absorption and during post-recessions. The resilience argument, then, may contribute to explain the rooted divide present in the Italian contemporary development: while more resilient regions are able to sustain virtuous growth paths, less resilient areas are affected by negative cumulative processes. It is worth noting that these results partially contrast with a recent contribution (Cellini and Torrisi, 2012), studying the resilience of Italian regions in terms of GDP in the very long-run (i.e. over the period 1890-2009).

From our discussion, two related questions naturally arise, which also represents possible speculative areas for future research: What are the determinants behind the geographical discrepancies in resilience? What policies are more desirable in presence of regional heterogeneity? The first question can be answered in several ways, highlighting the role of different industrial structures, the degree of international integration of a particular area and the importance of entrepreneurship spread at territorial level. The second issue concerns the adoption of place-tailored counter-cyclical and structural policies. The former have been discussed during the present crisis both in the US and in Europe, while the latter is the focus of the place-based paradigm in regional development. These questions are left for future research.

References

Artis M., C. Dreger, and K. Kholodilin (2011), What drives regional business cycles? The role of common and spatial components, *The Manchester School*, 79 (5):1035-1044.

Barrios S. and J.J. Lucio (2003), Economic integration and regional business cycles: Evidence from the Iberian regions, *Oxford Bulletin of Economics and Statistics*, 65(4):497-515.

Bassanetti A., M. Cecioni, A. Nobili, and G. Zevi (2010), Le principali recessioni italiane: un confronto retrospettivo, *Rivista di politica economica*, (7): 281-318.

Blanchard O.J., L.F. Katz, R.E. Hall, and B. Eichengreen (1992), Regional evolutions, *Brookings papers on economic activity*, 1992(1):1-75.

Burridge P. and I. Gordon (1981), Unemployment in the British metropolitan labour areas, *Oxford Economic Papers*, 33(2):274-297.

Caballero R.J. and M.L. Hammour (1994), The cleansing effect of recessions, *American Economic Review*, 84(5):1350-68.

Carlino G. and R. DeFina (1998), The differential regional effects of monetary policy, *Review of Economics and Statistics*, 80(4):572-587.

Cellini R. and R. Scorcu (1997), How many Italies? What data show about growth and convergence across Italian regions 1970-91, *Lavori di rassegna dell'Isco*, 1:93-124.

Cellini R. and G. Torrisi (2012), Regional resilience in Italy: a very long-run analysis, *Working Paper Portsmouth Business School*, University of Portsmouth, Portsmouth.

Cerra V. and S.C. Saxena (2008), Growth dynamics: the myth of economic recovery, *American Economic Review*, 98(1): 439-457.

Clark T.E. and E. Van Wincoop (2001), Borders and business cycles, *Journal of International Economics*, 55(1):59-85.

Congregado E., A.A. Golpe, and S.C. Parker (2009), The dynamics of entrepreneurship: hysteresis, business cycles and government policy, *Empirical Economics*, 1-23.

Cross R., H. McNamara, and A. Pokrovskii (2010), Memory of recessions, *Department of Economics Working Papers*, University of Strathclyde Business School.

De Haan J., R. Inklaar, and R. Jong-A-Pin (2008), Will business cycles in the euro area converge? A critical survey of empirical research, *Journal of Economic Surveys*, 22(2):234-273.

Fingleton B., H. Garretsen, and R. Martin (2012), Recessionary shocks and regional employment: Evidence on the resilience of UK regions, *Journal of Regional Science*, 52(1):109-133.

Glaeser E.L., G.A.M. Ponzetto, and K. Tobio (2011), Cities, skills, and regional change *NBER Working Paper*.

Göcke M. (2002), Various concepts of hysteresis applied in economics, *Journal of Economic Surveys*, 16(2):167-188.

Groot S.P.T., J.L. Möhlmann, JH Garretsen, and H.L.F. De Groot (2011), The crisis sensitivity of European countries and regions: stylized facts and spatial heterogeneity, *Cambridge Journal of Regions, Economy and Society*, 4(3):437-456.

Hamilton J.D. (2003), Comment on 'a comparison of two business cycle dating methods', *Journal of Economic Dynamics and Control*, 27(9):1691-1694.

Harding D. and A. Pagan (2003), A comparison of two business cycle dating methods, *Journal of Economic Dynamics and Control*, 27(9):1681-1690.

ISTAT (2004), *La Ricostruzione delle serie storiche dei principali indicatori del mercato del lavoro*, Rome.

Kalemli-Ozcan S., B.E. Sørensen, and O. Yosha (2001), Economic integration, industrial specialization, and the asymmetry of macroeconomic fluctuations, *Journal of International Economics*, 55(1):107-137.

Kim C.J. and C. Nelson (1999), Friedman's plucking model of business fluctuations: tests and estimates of permanent and transitory components, *Journal of Money, Credit and Banking*, 31(3):317-334.

Martin R. (2012), Regional economic resilience, hysteresis and recessionary shocks, *Journal of Economic Geography*, 12(1):1-32.

Martin R. and P. Sunley (1998), Slow convergence? the new endogenous growth theory and regional development, *Economic geography*, 74(3):201-227.

Mastromarco C. and U. Woitek (2007), Regional business cycles in Italy, *Computational Statistics & Data Analysis*, 52(2):907-918.

Miniaci R. and G. Weber (1999), The Italian recession of 1993: aggregate implications of microeconomic evidence, *The Review of Economics and Statistics*, 81(2):237-249.

Ng E.C.Y. (2010), Production fragmentation and business-cycle comovement, *Journal of International Economics*, 82(1):1-14.

Owyang M.T., J. Piger, and H.J. Wall (2005), Business cycle phases in US states, *The Review of Economics and Statistics*, 87(4):604-616.

Owyang M.T., D.E. Rapach, and H.J. Wall (2009), States and the business cycle, *Journal of Urban Economics*, 65(2):181-194.

Paci R. and A. Saba (1998), The empirics of regional economic growth in Italy: 1951-1993, *Rivista Internazionale di Scienze Economiche e Commerciali*, XLV, 5157542.

Panizza U., V. Cerra, and S.C. Saxena (2009), International evidence on recovery from recessions, *International Monetary Fund*, Number 2009-2183.

Partridge M.D., M. Boarnet, S. Brakman, and G. Ottaviano (2012), Introduction: Whither spatial econometrics? *Journal of Regional Science*, 52(2):167-171.

Redding S.J., D.M. Sturm, and N. Wolf (2011), History and industry location: Evidence from German airports, *The Review of Economics and Statistics*, 93(3):814-831.

Rossi S. (2010), Aspetti della politica economica italiana dalla crisi del 1992-93 a quella del 2008-09, *Giornata di Studi in onore di Guido M. Rey*, Bank of Italy, Rome.

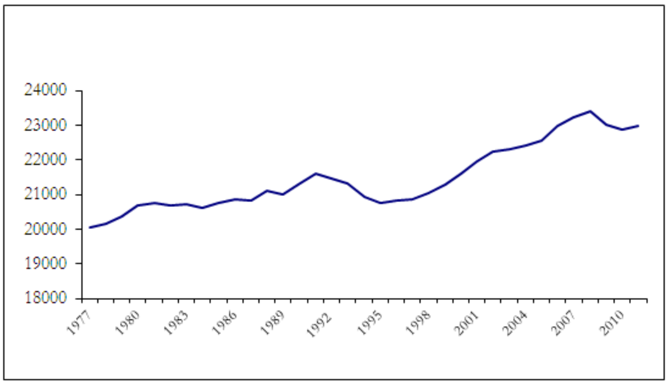
Simmie J. and R. Martin (2010), The economic resilience of regions: towards an evolutionary approach, *Cambridge Journal of Regions, Economy and Society*, 3(1):27-43.

Wilkerson C.R. (2009), Recession and recovery across the nation: lessons from history, *Federal Reserve Bank of Kansas City Economic Review*, Second Quarter, 5-24.

Tables and Figures

Figure 1. Italy Employment 1977 – 2011

(a) Level (Millions)



(b) Growth rate

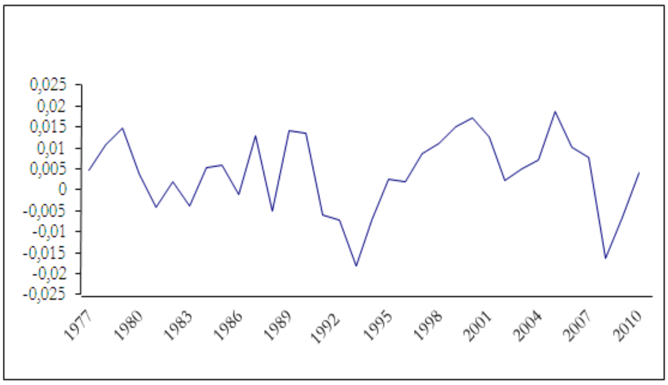


Figure 2. Italy Employment growth rate 1992(IV) – 2012(I)

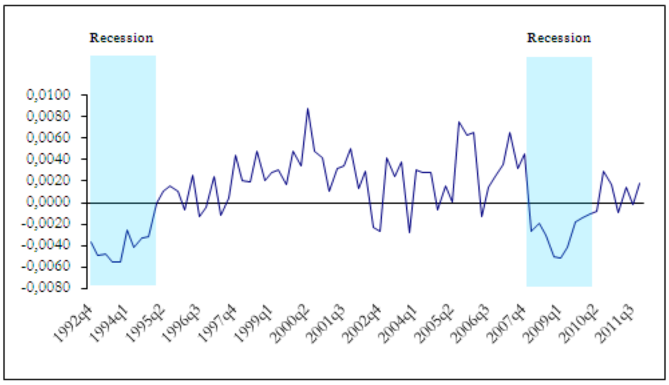
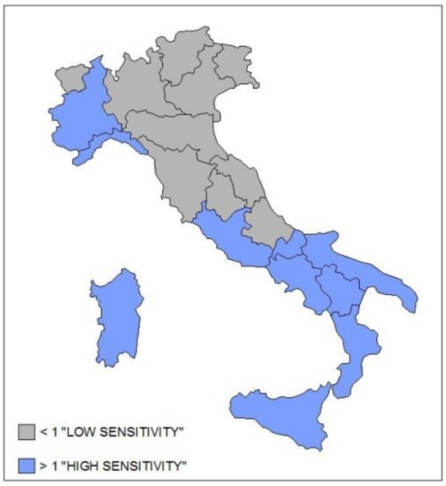


Figure 3. Italian sensitivity and recovery



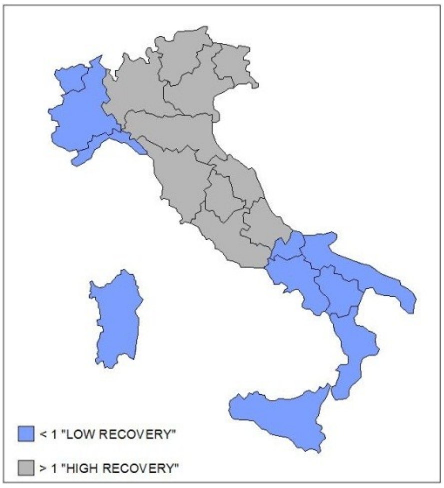
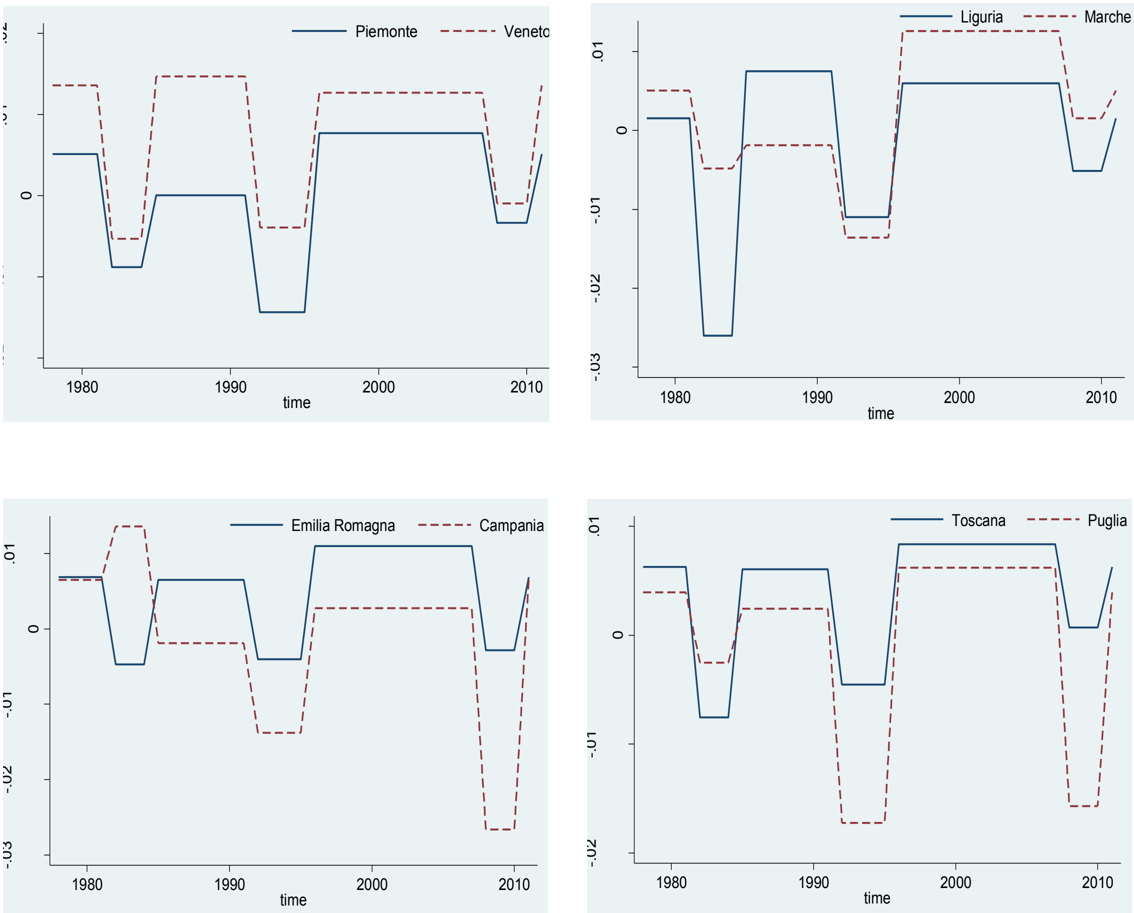
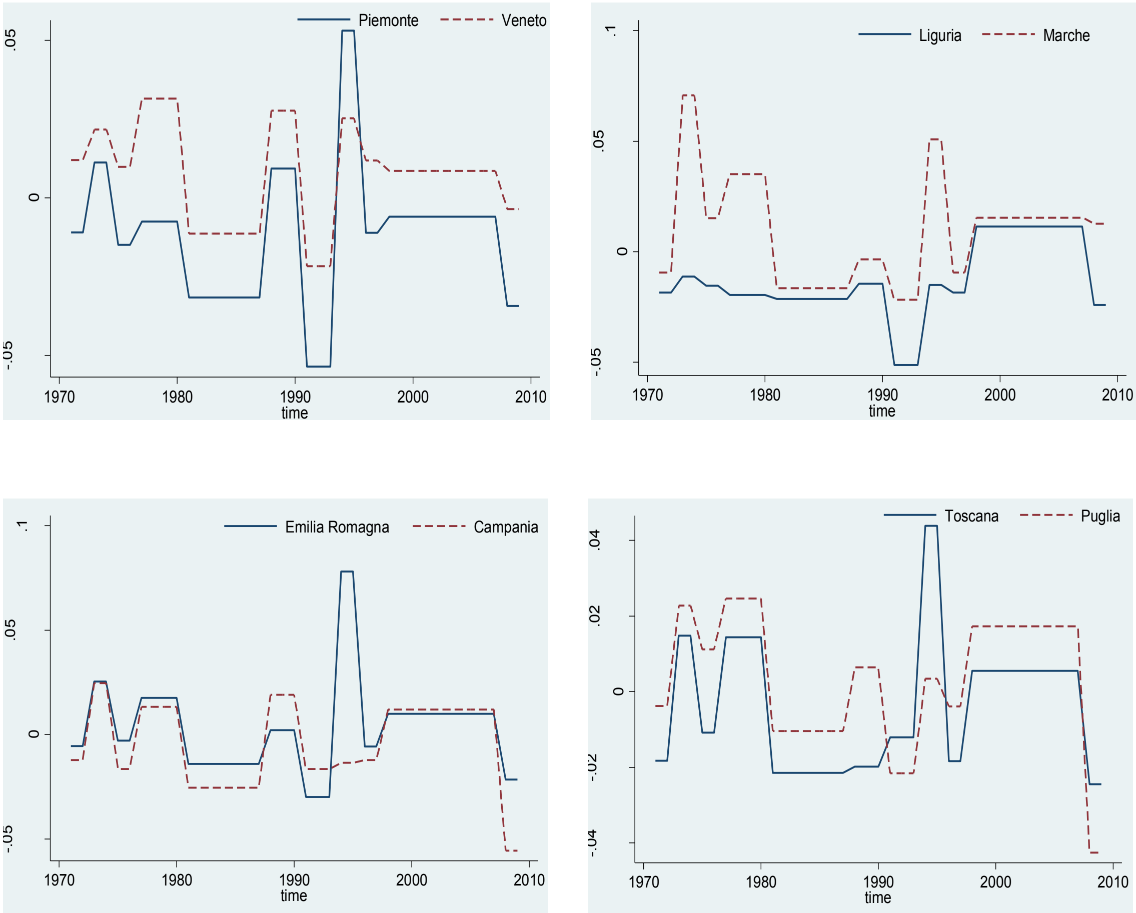


Figure 4. Selected regional comparisons SUR annual



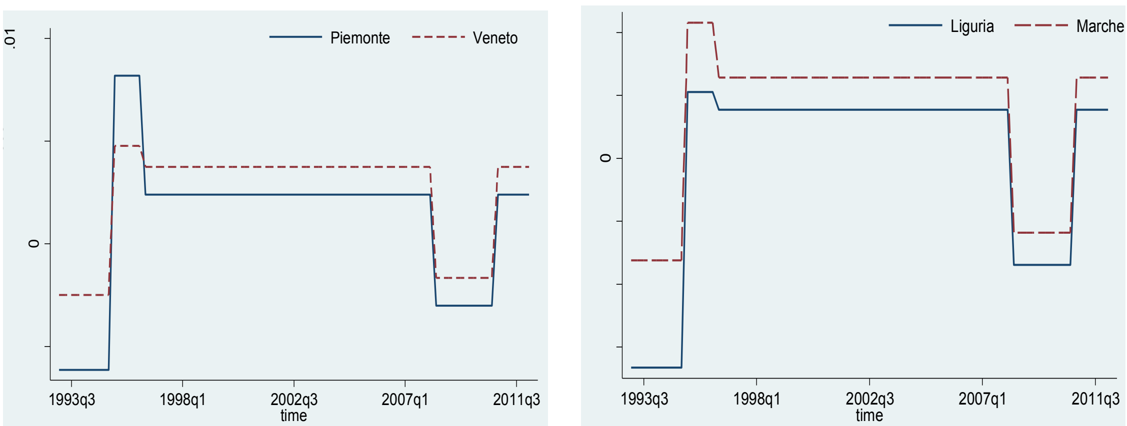
Note: Figure 4 reports the evolution of employment growth (y axis) from 1978 to 2011 (x axis) for selected Italian regions, obtained by estimating the SUR model in (1) for annual data.

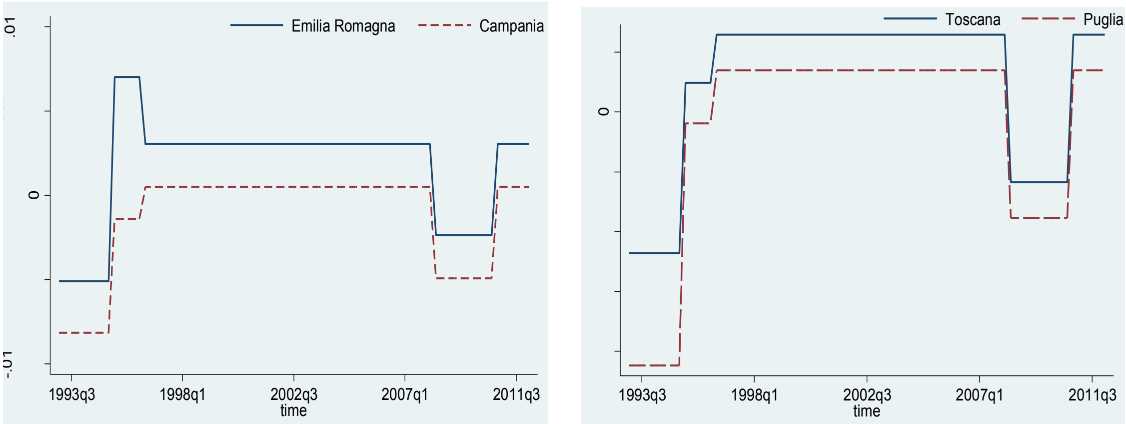
Figure 5. Selected regional comparisons SUR industry annual



Note: Figure 5 reports the evolution of industrial employment growth (y axis) from 1971 to 2009 (x axis) for selected Italian regions, obtained by estimating the unrestricted SUR model for industrial annual data.

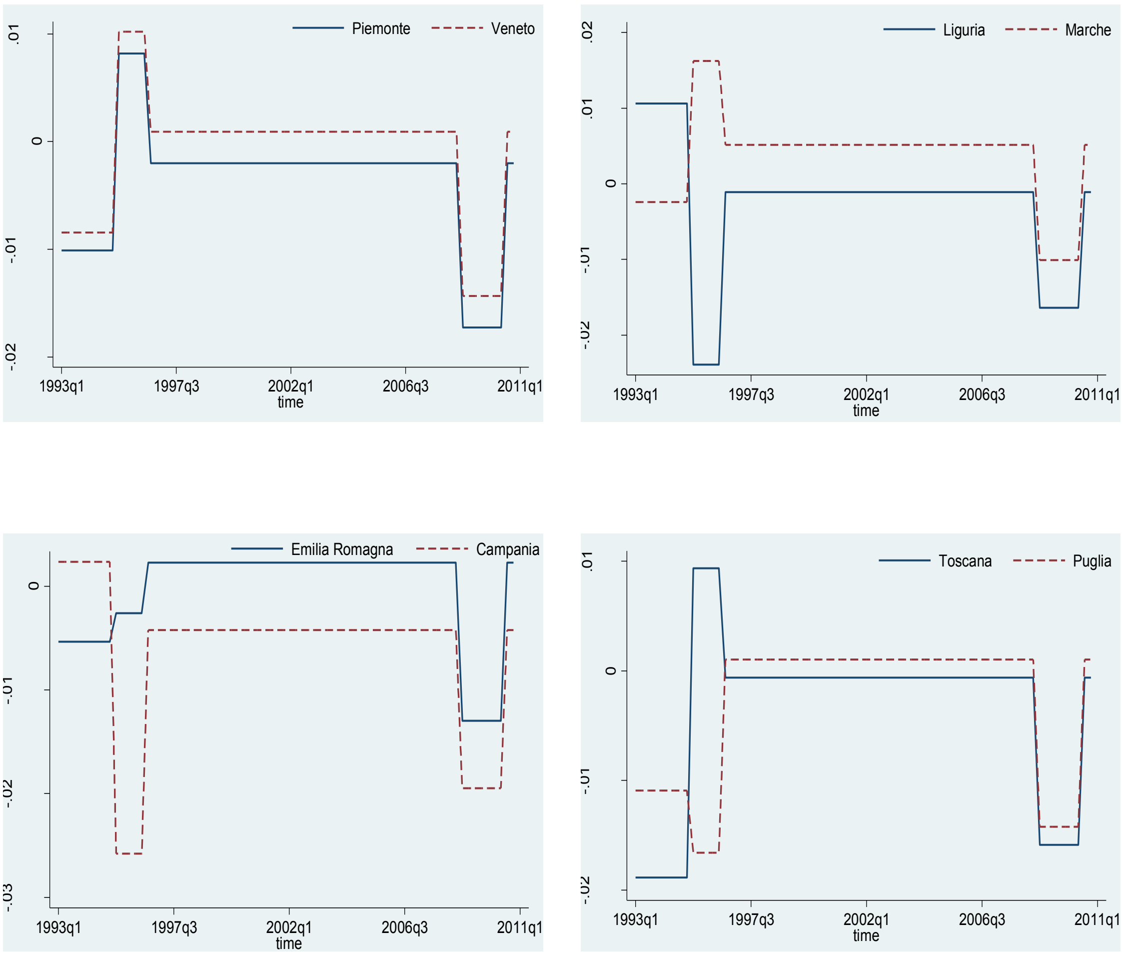
Figure 6. Selected regional comparisons SUR quarterly





Note: Figure 6 reports the evolution of employment growth (y axis) from 1993(I) to 2011(IV) (x axis) for selected Italian regions, obtained by estimating the SUR model for quarterly data.

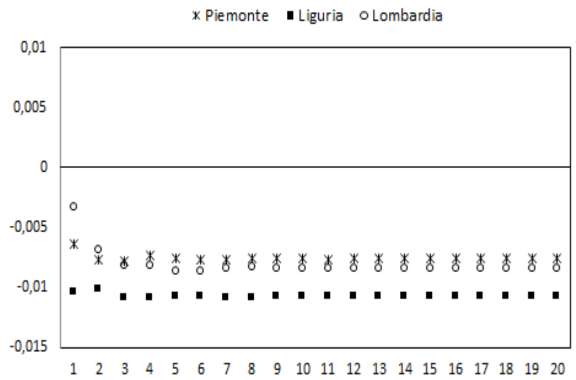
Figure 7. Selected regional comparisons SUR industry quarterly



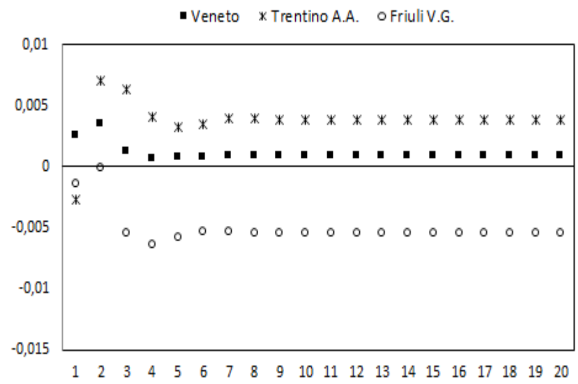
Note: Figure 7 reports the evolution of industrial employment growth (y axis) from 1993(I) to 2010(IV) (x axis) for selected Italian regions, obtained by estimating the SUR model for quarterly data.

Figure 8. Mean responses to Shocks from All regions

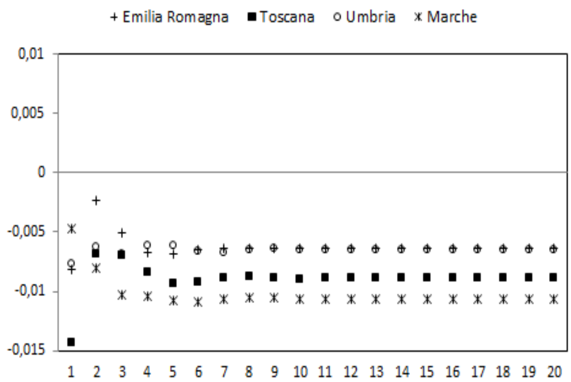
(a) North-West



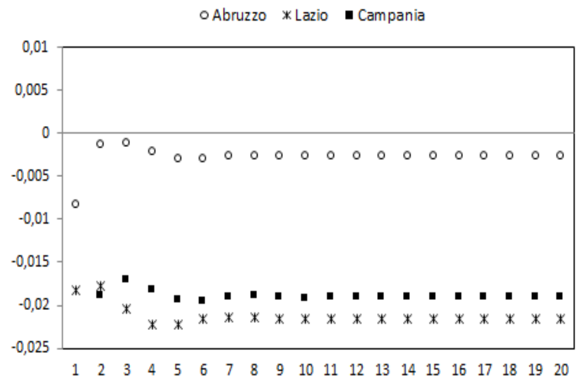
(b) North-East



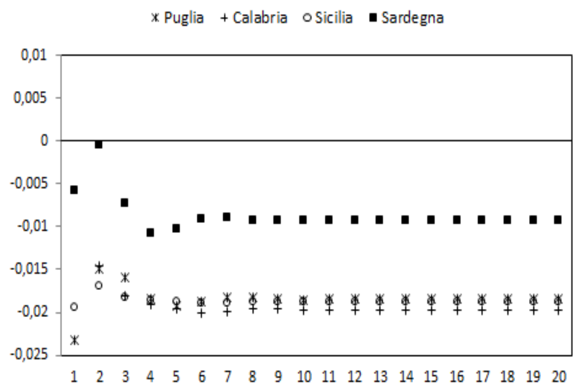
(c) Centre-North



(d) Centre-South



(e) South



Note: Figure 8 (a-e) reports the mean orthogonalized responses (y axis) over periods 1-20 (x axis), for five Italian macro areas, namely North-West, North-East, Centre-North, Centre-South and South.

Tables

Table 1. Italian Sensitivity Index

Region	1992(IV)-1995(I)	2008(II)-2010(III)
Piemonte	1.00	0.87
Valle d'Aosta	0.74	0.28
Lombardia	0.51	1.27
Liguria	1.10	0.77
Veneto	0.27	1.18
Trentino A.A.	0.66	0.21
Friuli V.G.	0.88	1.79
Emilia Romagna	0.87	0.15
Toscana	0.78	0.28
Umbria	0.16	1.53
Marche	0.53	0.74
Lazio	1.56	0.45
Abruzzo	0.84	2.04
Molise	2.30	1.96
Campania	1.39	1.42
Puglia	1.40	1.98
Basilicata	1.46	0.77
Calabria	1.70	0.78
Sicilia	1.86	0.77
Sardegna	1.08	0.87

Table 2. Italian Recovery Index

Region	1995(2)-2008(1)
Piemonte	0.88
Valle d'Aosta	0.84
Lombardia	1.15
Liguria	0.70
Veneto	1.44
Trentino A.A.	1.67
Friuli V.G.	1.02
Emilia Romagna	1.40
Toscana	1.02
Umbria	1.71
Marche	1.33
Lazio	1.86
Abruzzo	1.19
Molise	0.42
Campania	-0.09
Puglia	0.59
Basilicata	0.47
Calabria	0.03
Sicilia	0.84
Sardegna	0.86

Table 3. Mean Responses to Shocks from All Regions

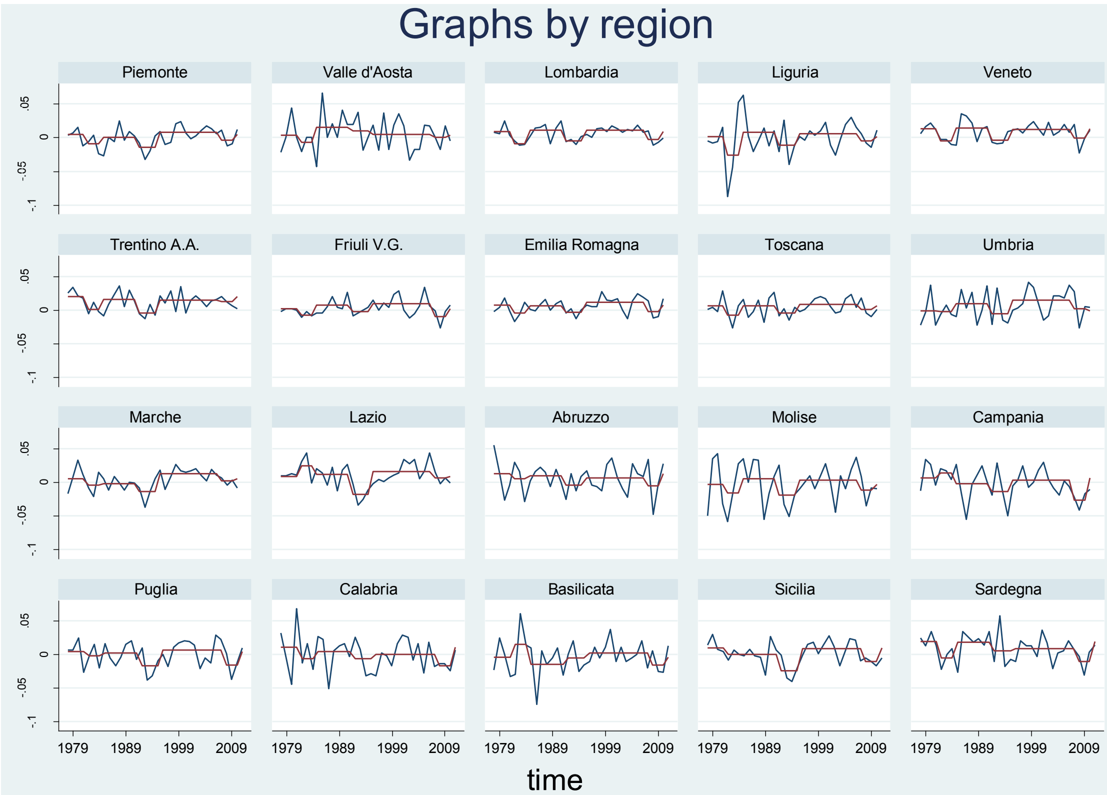
Region	Mean OIRF
Piemonte	- 0.00755
Liguria	- 0.01080
Lombardia	- 0.00806
Veneto	0.00105
Trentino A.A.	0.00379
Friuli V.G.	- 0.00486
Emilia Romagna	- 0.00625
Toscana	- 0.00829
Umbria	- 0.00654
Marche	- 0.01019
Abruzzo	-0.00279
Lazio	- 0.02119
Campania	- 0.01932
Puglia	- 0.01843
Calabria	- 0.01979
Sicilia	- 0.01868
Sardegna	- 0.00864

Appendix

I. SUR Results

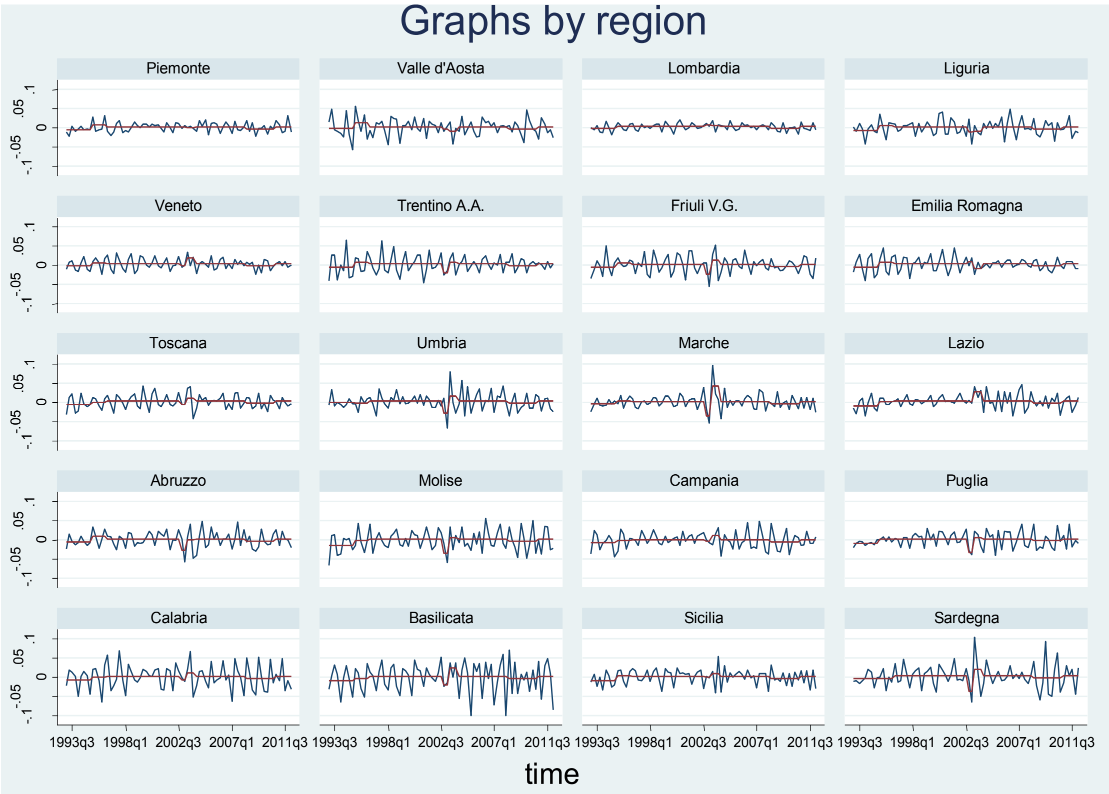
I.A SUR annual 1977-2011

Region	Auton. growth	Recession 1	Recession 2	Recession 3	Post 1	Post 2
Piemonte	0.00511	-0.01394	-0.01949	-0.00847	-0.00508	0.0025
Valle d'Aosta	0.00352	-0.01047	0.00616	-0.00342	0.01152	0.00125
Lombardia	0.00844	-0.01718	-0.01293	-0.01104	0.00312	0.00230
Liguria	0.00154	-0.02759	-0.01252	-0.00667	0.00105	-0.00090
Veneto	0.01358	-0.01890	-0.01752	-0.01454	0.00598	0.00444
Trentino A.A.	0.01984	-0.01886	-0.02433	-0.00747	-0.00458	-0.00570
Friuli V.G.	0.00189	-0.00400	-0.00916	-0.01213	0.00497	0.00712
Emilia Romagna	0.00689	-0.01158	-0.01092	-0.00973	-0.00039	0.00410
Toscana	0.00629	-0.01385	-0.01084	-0.00557	-0.0002	0.00207
Umbria	-0.00152	-0.00067	-0.00458	0.00358	0.01057	0.01559
Marche	0.00505	-0.00986	-0.01865	-0.00355	-0.0069	0.00755
Lazio	0.00817	0.01586	-0.02674	-0.00201	0.00384	0.00801
Abruzzo	0.01276	-0.00718	-0.01688	-0.01820	-0.00300	-0.00639
Molise	-0.00296	-0.01337	-0.01627	-0.00881	0.00838	0.00617
Campania	0.00652	0.00707	-0.02032	-0.03315	-0.00842	-0.00376
Puglia	0.00394	-0.0064	-0.02118	-0.01963	-0.00148	0.00226
Basilicata	0.01075	-0.01717	-0.01738	-0.02761	-0.00647	-0.01056
Calabria	-0.00384	0.01892	-0.00122	-0.0117	-0.01040	0.00613
Sicilia	0.01007	-0.0105	-0.03449	-0.02099	-0.00975	-0.00121
Sardegna	0.01954	-0.02423	-0.01410	-0.02987	-0.00198	-0.01142



I.B SUR quarterly 1992(IV)-2012(I)

Region	Auton. growth	Recession 1	Recession 2	Post 1
Piemonte	0.00194	-0.00802	-0.00493	0.00721
Valle d'Aosta	0.00087	-0.00537	-0.00493	0.01202
Lombardia	0.00268	-0.00579	-0.00493	0.00358
Liguria	0.00154	-0.00818	-0.00493	0.00057
Veneto	0.00323	-0.00486	-0.00493	0.00139
Trentino A.A.	0.00390	-0.00793	-0.00493	0.00529
Friuli V.G.	0.00179	-0.00711	-0.00493	0.00551
Emilia Romagna	0.00290	-0.00819	-0.00493	0.00447
Toscana	0.00258	-0.00729	-0.00493	-0.00160
Umbria	0.00329	-0.00424	-0.00493	-0.00596
Marche	0.00257	-0.00626	-0.00493	0.00173
Lazio	0.00426	-0.00136	-0.00493	-0.00194
Abruzzo	0.00184	-0.00695	-0.00493	0.00653
Molise	0.00099	-0.01497	-0.00493	-0.00341
Campania	0.00014	-0.00854	-0.00493	-0.00263
Puglia	0.00139	-0.09856	-0.00493	-0.00177
Basilicata	0.00061	-0.01094	-0.00493	-0.00309
Calabria	0.00095	-0.00980	-0.00493	-0.00038
Sicilia	0.00176	-0.01301	-0.00493	-0.00126
Sardegna	0.00292	-0.00949	-0.00493	-0.00808



II. Test results

II.A Augmented Dickey Fuller Test for unit root (1 lag) – quarterly data

Region	Test Statistics	MacKinnon p-value
Italia	-1.991	0.6062
Piemonte	-2.523	0.3166
VdA	-2.559	0.2990
Lombardia	-1.120	0.9257
Liguria	-3.072	0.1130
Veneto	-1.388	0.8643
Trentino A.A.	-3.360	0.0569
Friuli V.G.	-1.211	0.9081
Emilia Romagna	-2.945	0.1480
Toscana	-2.136	0.5261
Umbria	-2.959	0.1438
Marche	-0.722	0.9717
Lazio	-2.797	0.1981
Abruzzo	-3.150	0.0948
Molise	-3.022	0.1261
Campania	-1.239	0.9023
Puglia	-2.462	0.3471
Basilicata	-1.800	0.7049
Calabria	-2.302	0.4328
Sicilia	-1.613	0.7872
Sardegna	-1.853	0.6786

Note: Interpolated Dickey-Fuller critical value: 1% (-4.099); 5% (-3.477); 10% (-3.166).

II.B Optimal Lag length

Selection-order criteria
Sample: 1993q4 - 2012q1 Number of obs = 74

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2976.36				5.7e-54	-80.0367	-79.8504	-79.5697
1	3466.29	979.86	225	0.000	4.9e-57	-87.197	-84.2161	-79.7244*
2	3758.05	583.52	225	0.000	1.7e-57	-89.0014	-83.2258	-74.5231
3	4123.12	730.15*	225	0.000	4.0e-58	-92.7871*	-84.2169*	-71.3033
4	.	.	225	.	-7.8e-90*	.	.	.

Endogenous: Pie Lom Lig Ven Fri Emi Tos Umb Mar Laz Cam Pug Cal Sic Sar
Exogenous: _cons

II.C Lagrange Multiplier Test for residual autocorrelation

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	243.4371	225	0.19006
2	207.1558	225	0.79754
3	268.6737	225	0.02443
4	248.0057	225	0.13990

H0: no autocorrelation at lag order

II.D Eigenvalue Stability Condition

Eigenvalue stability condition

Eigenvalue	Modulus
1	1
1	1
1	1
1	1
1	1
1	1
.1030985 + .5530474*i*	.562575
.1030985 - .5530474*i*	.562575
.1543617 + .3662175*i*	.39742
.1543617 - .3662175*i*	.39742
.04494073 + .2720876*i*	.275774
.04494073 - .2720876*i*	.275774
-.04556488 + .2565802*i*	.260595
-.04556488 - .2565802*i*	.260595
.1701754	.170175

The VECM specification imposes 6 unit moduli.

II.E Tests for the normality of the errors

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_Lom	0.620	2	0.73351
D_Pie	3.975	2	0.13706
D_Lig	0.251	2	0.88192
D_Ven	1.888	2	0.38908
D_Fri	0.915	2	0.63294
D_Emi	0.762	2	0.68304
D_Tos	2.237	2	0.32670
D_Umb	0.658	2	0.71975
D_Mar	1.544	2	0.46215
D_Laz	2.151	2	0.34115
D_Cam	1.290	2	0.52457
D_Pug	14.053	2	0.00089
D_Cal	1.055	2	0.59018
D_Sic	0.832	2	0.65956
D_Sar	0.735	2	0.69235
ALL	32.967	30	0.32399

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_Lom	.06938	0.060	1	0.80623
D_Pie	-.56338	3.967	1	0.04639
D_Lig	.11037	0.152	1	0.69636
D_Ven	-.24191	0.732	1	0.39239
D_Fri	-.22937	0.658	1	0.41740
D_Emi	-.09772	0.119	1	0.72972
D_Tos	-.42249	2.231	1	0.13525
D_Umb	-.19122	0.457	1	0.49901
D_Mar	-.22036	0.607	1	0.43594
D_Laz	-.31608	1.249	1	0.26377
D_Cam	-.00636	0.001	1	0.98207
D_Pug	-.27328	0.934	1	0.33395
D_Cal	.27502	0.945	1	0.33088
D_Sic	.20123	0.506	1	0.47681
D_Sar	-.02076	0.005	1	0.94150
ALL		12.623	15	0.63136

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_Lom	2.5768	0.560	1	0.45440
D_Pie	2.9517	0.007	1	0.93200
D_Lig	2.822	0.099	1	0.75301
D_Ven	2.3917	1.156	1	0.28221
D_Fri	3.2868	0.257	1	0.61210
D_Emi	2.5464	0.643	1	0.42262
D_Tos	2.9554	0.006	1	0.93720
D_Umb	2.7466	0.201	1	0.65419
D_Mar	2.4525	0.937	1	0.33311
D_Laz	2.4627	0.902	1	0.34224
D_Cam	2.3575	1.290	1	0.25608
D_Pug	5.049	13.120	1	0.00029
D_Cal	2.813	0.109	1	0.74103
D_Sic	2.6769	0.326	1	0.56790
D_Sar	2.5167	0.730	1	0.39290
ALL		20.343	15	0.15916

An exploratory analysis on the determinants of regional resilience in Italy

Abstract

A structural econometric framework is presented for detecting and measuring economic resilience in its twin sense. Engineering resilience is modelled as the speed of adjustment to the long-run equilibrium obtained by estimating a linear **VECM** appropriately defined. Ecological resilience is identified as the degree of tolerance between regimes in a non-linear smooth-transition autoregressive **STAR** model. A set of explanatory variables contributes to explain the causes behind the divergent resilient employment dynamics showed by Italian regions in the last thirty years. Spatial interactions among neighbouring regions are also considered in the analysis. 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.

I. Introduction

During recessionary times the relation between negative shocks and economic growth usually regains its importance among academics and policymakers (recently, Cerra and Saxena, 2008; 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 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.

Despite economic resilience has been explicitly addressed by many recent contributions, some thorny aspects still need to be explained in order to provide a more coherent research framework and a useful starting point for suggesting policy proposals. Apart from few deserving attempts (Reggiani *et al.*, 2002; Martin, 2012), economic resilience suffers from the lack of a robust theoretical structure, which is a prerequisite for a better understanding of every phenomenon at hand. Moreover, 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 an 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 approach.

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, canonical 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 neighbourhood areas.

This specification is then applied to study the causes behind the divergent resilient employment dynamics showed by Italian regions in the last thirty years, as it has been documented in a companion working paper. Traditional explanations such as the industrial structure 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 of explaining growth differences across Italian regions.

Three are the main purposes of this contribution. 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 arguments

Explaining the various consequences of a crisis implies answering two related questions: what is the magnitude of a given recession in terms of output? How can we separate the short and long term effects associated to a particular crisis? Both these questions represent the starting point for assessing the overall impact of a crisis on the economic activity of a given area or sector. And, the same answers result helpful as a preliminary step to subsequently find out the determinants behind different levels of shock-absorption and shock-persistence.

Before proceeding in this direction, however, it seems crucial to correctly identify the nature and the length of each shock. For instance, currency crises are very different from banking crises if we consider both their origins and effects (Calvo and Reihnart, 2002). While the former have direct implications for trade and public finances, the latter mainly influence credit availability and agents' expectations in financial markets. Moreover, short recessions may have diverse implications than long-lasting negative events (Mueller, 2012): few quarters are not synonymous for many years.

In addition, fiscal and monetary policy interventions may require diverse approaches and instruments according to the characteristics and the duration of different recessions. A clear evidence of this aspect has been provided by the wide and differentiated spectrum of measures adopted since the financial crisis started in 2007. After the initial decisions undertook by policymakers in the US and in Europe for dealing with banking failures and financial destabilization, since 2010 several policies have been addressed to solve sovereign debt problems (in some European countries) and re-launch economic growth and employment (particularly, in the US and Japan).

Insert about here.
Figure 1. GDP growth and recessions in Italy, 1970(I) – 2012(IV).

Figure 1 illustrates the dynamics of real GDP growth in Italy from 1970(I) to 2012(IV). Shadow areas represent the four main recessions experienced in Italy in the last four decades, defined as two or more consecutive quarters with relevant negative GDP growth rates. The first recessionary event is associated to the first oil shock of early Seventies. In the first half of 1990s, a currency crisis (the so-called *Lira* crisis) hit the Italian economy, amplified by some internal and external destabilizing adverse occurrences. The last two crises are part of the ongoing Great Recession: after the financial turmoil started in 2007, since the first half of 2011 the Italian economy has been involved in a sovereign debt crisis jointly with the Euro crisis.

The various relations between growth and shocks arising from different kinds of crises can be described by means of a simple exercise based upon the recent contribution of Cerra and Saxena (2008)[1]. Considering economic output (employment or GDP) as a nonstationary process (Nelson and Plosser, 1982), we estimate a univariate autoregressive AR(p) model in growth rates for the Italian case in order to obtain impulse response functions for different recessionary events[2].

In particular, the following model has been estimated:

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{J} \beta_j \Delta y_{i,t-j} + \sum_{s=0}^{S} \gamma_s D_{t-s} + \varepsilon_{it} \tag{4.1}$$

where Δy_{it} is the percentage change in employment in the macro-region i (North-West, North-East, Centre, South[3]) at time t, and D is a dummy variable denoting a given crisis (oil crisis, currency *Lira* crisis, financial crisis, debt and Euro crises). 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[4]; 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 the Italian aggregate employment series. Naturally, this timing does not perfectly coincide with the identification of shocks from GDP series[5].

Insert about here.
Figure 2. Impulse Responses: Italian recessions, 1977(I) – 2012(IV).

[1] 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 Panizza *et al.* (2013).

[2] More precisely, 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.

[3] Employment series covering such a long time span are available only at macro-regional level. These four aggregations have been classified by the Italian national institute of statistics (ISTAT): 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.

[4] Concerning regional differences in prices, Cecchetti et al. (2002) have outlined several reasons behind this aspect: i) formal and informal trade barriers; ii) presence of local monopoly; iii) transportation costs; iv) the presence of non-traded goods in the general price level and the potential for differential growth in the level and efficiency of factors used in their production.

[5] The identification of each recessionary event analyzed in this section is based upon the exogenous approach (Harding and Pagan, 2003): crises have been detected by combining the observation of output series with the official timing of Italian recessions provided by the Bank of Italy. More specifically: 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).

Figure 2 (a-d) illustrates the different behaviour showed by the four Italian macro-regions during every crisis in terms of responses to a one unit negative employment shock. Despite these results are reported only for illustrative purposes, two main comments are 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. These aspects will be further investigated in next sections.

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. Moreover, 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.

Interestingly, the third generation of real business cycle models (Farmer, 2012; Plotnikov, 2013) is aimed to introduce multiple equilibria in unemployment departing from the canonical business cycle framework. These models rely upon assumptions specific to the 'Old Keynesian Economics' (Farmer 2008), where the natural rate hypothesis does not hold and deviations of the unemployment rate from its optimal value may be permanent.

Whether or not employment losses are reversed after a specific adverse shock is an historical issue within the economic debate. On the one side, traditional real business cycle models are built upon the assumption of supply-driven TFP shocks or neutral technology shocks (Justiniano *et al.*, 2010) and the natural rate hypothesis regarding unemployment

(Plosser, 1989)[6]. According to this framework, recessions are temporary random fluctuations in the rate of technological change, corresponding to periods of 'chronic laziness' (Mankiw, 1989).

Every unpredicted disturbance is able to impose a reduction in the level of a variable for a certain period, but its structural trend is re-established in the long run (peak-reversion effect). As a consequence, a decline in GDP or employment does not influence an economy in a perpetual way, given that the system is involved in a self-equilibrating continuous process. Engineering resilience captures this transient aspect: how a country or a region is able to regain its stable growth pattern in the long-run.

On the other side, permanent losses arising from adverse shocks are typically analyzed by means of multiple equilibria models, nonlinear regimes and hysteresis in unemployment (Ball, 2009; Sinclair, 2009; Morley and Piger, 2012). Since the seminal contribution of Beaudry and Koop (1993) the question why recessions may have a long impact on a given environment has risen in importance. In other words, jobless recoveries 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)[7].

When the negative consequences of a crisis become persistent not dying out over time, the intrinsic evolution of the economy itself is at stake. Recessions, then, represent turning points in the dynamic of a particular variable such as GDP or employment. Unemployment duration, human and physical capital retrenchment, deterioration of terms of trade and distorted expectations are some channels capturing the permanent impact of adverse shocks. Ecological resilience is focused on analysing the enduring characteristics derived from a particular crisis.

Several explanatory variables can contribute to describe why a particular context follows or not a specific post-recessionary adjustment path. For instance, comparing the

[6] To be more precise, subsequent extensions of RBC models have introduced endogenous propagation mechanisms of shocks in order to describe a continuum process for achieving the unique steady state (Farmer and Guo, 1994) and several labour market frictions in the spirit labour matching models.

[7] Various sources of hysteresis have been analyzed in the literature: i) path dependence and the formation of preferences; ii) insider-outsider effects in wage determination; iii) depreciation of skills and search effectiveness; iv) path dependent stigma effects; v) labour hoarding and labour market tightness; vi) firing costs and voluntary quits; vii) institutional effects of cyclical unemployment; viii) capital formation and the equilibrium rate of unemployment. From an empirical perspective, the main approaches for identifying hysteresis are: a) testing for unit roots in the rate of unemployment; b) testing for non-linear dynamics and multiple equilibria in the labour market; c) testing for duration dependence in the employment probability; d) testing for insider-outsider effects in wage formation. For a more detailed discussion, see Røed (1997).

speed of out-flow migration and that of firms' attraction after a negative shocks on employment can shed light on the long run effects of a crisis (Blanchard *et al.*, 1992). Moreover, a decline in the capital stock (human and physical) caused by an adverse event can explain the long-lasting impact of a recession (Rowthorn, 1999)[8]. Higher interest rates and increased credit constraints act in the same direction for hampering economic recovery.

The analysis of economic resilience at regional level represents a promising way of studying the relations between shocks and unemployment disparities among regions within the same country. And, this can result helpful in order to suggest policy proposals able to reducing unemployment differentials at territorial level, increasing national output and lowering inflationary pressure (Taylor, 1996). Not so surprisingly, then, in recent times several contributions have directly investigated local labour market dynamics (Moretti, 2011), regional business cycles issues (Hamilton and Owyang, 2012) and the link between long term unemployment and region-specific factors (Greenaway-McGravy and Hood, 2013).

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.

In this framework, 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[9]. In other words, the idea of linear cointegration identifies the magnitude of the disequilibrium error from one period that is corrected in the next one.

[8] The relationships between capital shortage and unemployment is an historical one within the economic debate and it is mainly focused on the inelasticity of factors substitution between labour and capital (Bean, 1989; Rowthorn, 1999; Stockhammer and Klaar, 2011).

[9] For a more detailed discussion on the equilibrium implications of cointegration see Beyer and Farmer (2007) and Morley (2007).

Moreover, the error correction representation allows to distinguish between short-run and long-run components of each relation.

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 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 the next section 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[10]. For a more detailed discussion, see Potter (1999), 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[11] is:

$$y_t = \phi_1' y_t^{(p)} \left(1 - G(s_t; \gamma, c)\right) + \phi_2' y_t^{(p)} G(s_t; \gamma, c) + \varepsilon_t \tag{4.2}$$

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:

$$G(s_t; \gamma, c) = \{1 + exp[-\gamma \prod_{k=1}^{N} (s_t - c_k)]\}^{-1}, \qquad \gamma > 0 \tag{4.3}$$

with γ denoting the speed of transition between regimes[12], N the total number of transition points, s_t the transition variable[13] and c_k the threshold(s) value(s) indicating the level of the transition variable at which a transition point occurs.

The LSTAR model obtained by combining (4.2) and (4.3) represents, at any given point in time, the evolution of the variable y_t as a weighted average of two different linear

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[10] Acemoglu and Scott (1994), among others, highlights (at least) three different reasons for motivating the presence of nonlinearities in the business cycle: i) different types of shocks may operate at different stages of the cycle; ii) the propagation mechanism may change over the cycle; iii) the way the economy responds to a positive shock compared to a negative shock may be asymmetric.

[11] The analysis hereafter presented is based upon a simple version of the STAR model. It is worth mentioning, however, the possibility of extending the model in (6) 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).

[12] Three features of the parameter γ are worth noting: i) $\gamma > 0$ is an identifying restriction; ii) when $\gamma \to 0$ the model in (6) 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 $s_t > c$.

[13] The transition variable s_t can be a lagged endogenous variable (y_{t-d}, $d > 0$), a linear/nonlinear representation of lagged endogenous variables, a linear trend or an exogenous variable. For a more complete discussion on this, see Teräsvirta, 1994.

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 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[14]. 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 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

[14] 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).

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 large number of observations (t=81) for the 20 Italian regions (NUTS II). Employment series are also available at regional level for specific sectors (agriculture, manufacturing, services) for the period 1992(IV) – 2010(IV) with (t=73). The main data source for employment 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, together with graphs showing differences in employment growth between regions and the Italian aggregate.

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, Campania and Lazio are characterized by the lowest degree 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) specify a linear $AR(p)$ model for the dependent variable under analysis; b) test the null hypothesis of linearity against the alternative of STAR[15]; c) if linearity is rejected, define the appropriate transition function; d) estimate the model by conditional maximum likelihood (or nonlinear least squares); e) conduct 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.

15 As firstly proposed by Luukkonen et al. (1988), the test for detecting nonlinearity is based upon a third-order Taylor approximation of the underlying process under the null hypothesis of linearity.

The presence of nonlinearity has been rejected for four regions, namely Valle d'Aosta, Trentino A.A., Friuli V.G. and Basilicata[16]. 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[17].

At a first glance, we can observe differences in the delay parameter d across regions, denoting diverse 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. For more details on the estimation results, see 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 (e.g. 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

[16] 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).

[17] Complete estimation results are available from the author upon request.

the transition occurs at lower values: these regions (negatively) change their 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 nonlinear framework. Liguria, for instance, continues to register a low level of resilience, though this region is in the North of Italy. In a symmetric way, Puglia (and, even Sardegna) shows 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 3. Selected smooth transition functions.

As an illustrative example, figure 3 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 administration. 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[18]. 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 tradable goods and non-public services.

We measure the importance of trade for economic resilience by using an index based upon the revealed comparative advantage approach as theorized by Hausmann and Rodrik (2003). The main intuition behind this perspective is that some traded goods are associated with higher productivity levels than others and that countries (regions) that latch

[18] The Krugman absolute specialization Index (KI) measures the economic structure of one region/country with respect to a given reference group. A simple version is calculated as $\sum_{n=1}^{N} |s_{nj} - s_{nk}|$, where n denotes an industry, j a given region, k the reference group (in our case, the Italian aggregate) and s is the share of regional sector-specific employment or added value. One interesting property of the Krugman Index is that the introduction of more disaggregated industrial structures does not alter the degree of specialization. An higher level of the KI is associated to a wider difference in the degree of specialization between a given region and the reference group.

on the higher productivity goods will perform better than those lagging behind (Hausmann et al., 2007).

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

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

where regional per-capita GDP is weighted by the revealed comparative advantage of each region in good j[19].

Subsequently, for each region it is obtained an index called *EXPY* which ranks traded goods in terms of their implied productivity or, in other words, that can be interpreted as an inverse of the well-known Balassa revealed index. In particular, 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 our purposes, we collect data on the export basket for the 20 Italian regions for the period 1992 – 2012. We have detailed observations for 38 product categories (see the Appendix) exported to the rest of the world. For both time horizons previously presented we construct two measures for exports: *EXPY*, considering all the product categories; *MADEITALY*, limiting the observation to 17 product categories which represent the

[19] As noted by Di Maio and Tamagni (2008), the *PRODY* index represents a sector-specific measure for all the countries (regions) considered. Moreover, sectors with high values of *PRODY* denotes more sophisticated activities where high productive (and income) regions play a major role in terms of exports.

traditional 'Made in Italy' activities such as machineries, mechanicals, design and creative industries[20].

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[21]. For the 20 Italian regions we have Census data (source ISTAT) covering the period 1991 – 2011[22].

The variable capturing entrepreneurial human capital (*HUMCAPENTR*) has been obtained as in Gennaioli et al. (2013), measuring the percentage of directors/managers and bureaucrats with a college degree. These data are referred to the Census year 2001 and they derive from the International IPUMS database. A more exhaustive discussion regarding the human capital variables is presented in the section on the empirical results, together with the description of the possible endogeneity issues linked to human capital (i.e. given the relation between migration and economic development).

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[20] More precisely, the variable *MADEITALY* hereafter used combines 13 product categories (e.g. food and taste, machineries, electronics, etc.) usually defined as traditional Made in Italy (Rapporto ICE, 2013) with 4 product categories related to creative industries such as editing and museums. A similar extended version of Made in Italy has been recently applied by two Foundations (*Fondazione Edison* and *Symbola*) for mapping Made in Italy at district level. Practically, however, the difference between the two definitions is of secondary importance for the empirical analysis.

[21] More precisely, our dataset contains four educational levels (primary, lower secondary, upper secondary, tertiary) corresponding to the UNESCO ISCED 1 – 2 – 3 – 5, respectively. For each educational level, the corresponding duration in years has been defined as follows: primary (5 years); lower secondary (primary duration + 3 years); upper secondary (primary and lower secondary cumulated duration + 5 years); tertiary (cumulated duration up to upper secondary + 4 years).

[22] 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. Additional results are available upon request.

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[23].

Our measure of civic capital at regional level (*CIVIC*) is the electoral participation to referenda registered in the Italian regions over the period under consideration[24]. 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. However, we also use the number of blood donations divided for the population (> 15 years) at regional level as a complementary measure. Since the seminal contribution of Richard Titmuss (1970), blood donations have represented affordable proxies for inferring social and civic aspects.

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

As a proxy for the level of financial constraints showed by Italian regions 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

[23] An additional benefit related to the presence of civic capital has been recently stressed by Philippe Aghion et al. (2010) which have noted that when people expect to live in a civic community they also expect low levels of regulation and corruption.

[24] 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.

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 at first glance, 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[25].

[25] 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

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 regions like Emilia Romagna, Toscana, Veneto and Marche show the highest level 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 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.

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.

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:

$$\boldsymbol{y} = \gamma \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \beta + \boldsymbol{u} \tag{4.4}$$

$$\boldsymbol{u} = \rho \boldsymbol{M} \boldsymbol{u} + \boldsymbol{\varepsilon} \tag{4.5}$$

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[26], $\boldsymbol{u}$ 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[27] 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 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

26 In the following analysis it is assumed, without loss of generality, a unique spatial weight matrix, namely $\boldsymbol{W} = \boldsymbol{M}$.
27 The Moran's I global index has been preferred with respect to other spatial measures such as the Getis & Ord's global index or the Geary's C, given that the latter two indices require a spatial matrix in binary form which is not suitable to analyse the Italian case.

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.

Tables 8 (A – D) report spatial estimation results for engineering resilience obtained by applying Maximum Likelihood estimator. From the previous discussion, it results more appropriate to investigate spatial effects by looking at engineering resilience. 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 need to be further clarified by investigating the reasons behind spatial effects of shocks. However, this and other questions are left for future research.

V. Conclusion

Paraphrasing Romer and Romer (1994), this paper has been developed around the twin research question: where and why recession ends? 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 across Italian regions. Temporary and persistent effects have been distinguished by applying two complementary econometric procedures, namely linear and nonlinear. A set of explanatory variables has contributed to shed light on the determinants of resilience. 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. 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.

As possible avenues for future research, 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 incorporating spatial interactions among regions in a more structured way and focusing on possible forecasting speculations. Moreover, a natural further step of investigation is the analysis of the place-specific effects related to fiscal and monetary policies. These and other questions on both the theoretical and empirical side are left for future research.

References

Angulo A., J. Mur, J. Trivez and M. Atwi (2013), Forecasting heterogeneous regional data: the case of Spanish employment, *paper presented at the 6th J. Paelinck Seminar*, Autonomous University of Madrid.

Ball L.M. (2009), Hysteresis in unemployment: old and new evidence, *NBER working paper*, n. 14818.

Barca F., P. McCann and A. Rodríguez-Pose (2012), The Case for Regional Development Intervention: Place-Based versus Place-Neutral Approaches, *Journal of Regional Science*, 52(1):134-52.

Barro R.J. and J.W. Lee (2012), A new dataset of educational attainment in the world, 1950 – 2010, *Journal of Development Economics*.

Beaudry P. and G. Koop (1993), Do recessions permanent change output?, *Journal of Monetary Economics*, 31: 149-163.

Blanchard O.J., L.F. Katz, R.E. Hall, and B. Eichengreen (1992), Regional evolutions, *Brookings papers on economic activity*, 1992(1):1-75.

Blanchard O.J. and L.H. Summers (1987), Hysteresis in unemployment, *European Economic Review*, 31(1-2): 288-295.

Calvo G.A., F. Coricelli and P. Ottonello (2012), The labor market consequences of financial crises with or without inflation: jobless and wageless recoveries, *NBER Working Paper n. 18480*.

Calvo G.A. and C.R. Reinhart (2002), Fear of floating, *Quarterly Journal of Economics*, 117(2): 379-408.

Cerra V., U. Panizza and S.C. Saxena (2013), International evidence on recovery from recessions, *Contemporary Economic Policy*, 31(2): 424-439.

Cerra V. and S.C. Saxena (2008), Growth dynamics: the myth of economic recovery, *American Economic Review*, 98(1): 439-457.

Escribano A. (2004), Nonlinear error correction: the case of money demand in the United Kingdom (1878 – 2000), *Macroeconomic Dynamics*, 8: 76 – 116.

Farmer R.E.A. and J.T. Guo (1994), Real Business Cycles and the Animal Spirits Hypothesis, *Journal of Economic Theory*, 63: 42-73.

Farmer R.E.A. (2008), Old Keynesian Economics, in *Macroeconomics in the Small and the Large*, ed. by R.E.A. Farmer, ch. 2, pp. 23-43, Edward Elgar, Cheltenham, UK..

Farmer R.E.A. (2012), The evolution of endogenous business cycles, *NBER working paper*, n. 18284.

Ferrara L., M. Marcellino and M. Modigliani (2013), Macroeconomic forecasting during the Great Recession: the return of non-linearity?, *CEPR Discussion Paper n. DP9313*.

Fingleton B., H. Garretsen, and R. Martin (2012), Recessionary shocks and regional employment: Evidence on the resilience of UK regions, *Journal of Regional Science*, 52(1):109-133.

Fingleton B. and S. Palombi (2013), Spatial panel data estimation, counterfactual predictions, and local economic resilience among British towns in the Victorian era, *Regional Science and Urban Economics*, 43:649-660.

Gennaioli N., R. La Porta, F. Lopez-de-Silanes and A. Shleifer (2013), Human capital and regional development, *Quarterly Journal of Economics*, 128(1): 105-164.

Giannola A. and A. Lopes (2012), Banca, sistema produttivo e dualismo in Italia. Continuità e mutamenti strutturali in una prospettiva di lungo periodo, in SVIMEZ (ed.), *Nord e Sud a 150 anni dall'Unità d'Italia*, Roma.

Guiso L., P. Sapienza and L.Zingales (2010), Civic capital is the missing link, *NBER Working Paper n. 15845*.

Hamilton J.D. and M.T. Owyang (2012), The propagation of regional recessions, *Review of Economics and Statistics*, 94(4): 935-947.

Hausmann R. and C.A. Hidalgo (2010), Country diversification, product ubiquity, and economic divergence, *Working Paper Series 10-045*, J.F. Kennedy School of Government, Harvard University.

Hausmann R., J. Hwang and D. Rodrik (2007), What you export matters, *Journal of Economic Growth*, 12: 1-25.

Hausmann R., F. Rodriguez and R. Wagner (2008), Growth Collapses, in C.M. Reinhart, C.A. Végh and A. Velasco (eds), *Money, Crises and Transition Essays in Honour of G.A. Calvo*, MIT Press, Cambridge (MA), USA.

Hausmann R. and D. Rodrik (2003), Economic development as self-discovery, *Journal of Development Economics*, *72*(2), 603-633.

Justiniano A., G.E. Primiceri and A. Tambalotti (2010), Investment shocks and business cycles, *Journal of Monetary Economics*, 57(2): 132-145.

Kang W., D.A. Penn and J. Zeitz (2012), A regime-switching analysis of the impact of oil price changes on the economies of U.S. States, *The Review of Regional Studies*, 41, 81 – 101.

Mankiw N.G. (1989), Real business cycles: a new-Keynesian perspective, *Journal of Economic Perspective*, 3(3):79-90.

Martin R. (2012), Regional economic resilience, hysteresis and recessionary shocks, *Journal of Economic Geography*, 12(1):1-32.

Moretti E. (2011), Local labor markets, *Handbook of Labor Economics*, 4:1237-1313.

Morley J. and J. Piger (2012), The asymmetric business cycle, *The Review of Economics and Statistics*, 94(1): 208-221.

Mueller H. (2012), Growth dynamics: the myth of economic recovery – comment, *American Economic Review*, 102(7): 3774-3777.

Potter S.M. (1999), Nonlinear time series modelling: an introduction, *Journal of Economic Surveys*, 13(5): 505 – 528.

Plotnikov D. (2013), Hysteresis in unemployment and jobless recoveries, *UCLA working paper*.

Reggiani A., T. De Graaf and P. Nijkamp (2002), Resilience: an evolutionary approach to spatial economic systems; *Networks and Spatial Economics*, 2(2): 211-229.

Rodrik D. (2013), Unconditional convergence in manufacturing, *Quarterly Journal of Economics*, 128(1): 165-204.

Sinclair T.M. (2009), Asymmetry in the business cycle: Friedman's Plucking model with correlated innovations, *Studies in Nonlinear Dynamics and Econometrics*, 14(1).

Simmie J. and R. Martin (2010), The economic resilience of regions: towards an evolutionary approach, *Cambridge Journal of Regions, Economy and Society*, 3(1):27-43.

Skalin J. and T. Teräsvirta (2002), Modeling asymmetries and moving equilibria in unemployment rates. *Macroeconomic Dynamics*, 6(2): 202 – 241.

Teräsvirta T. (1994), Specification, estimation and evaluation of smooth transition autoregressive models, *Journal of the American Statistical Association*, 89: 208 – 218.

van Dijk D. and P.H. Franses (1999), Modeling multiple regimes in the business cycle, *Macroeconomic Dynamics*, 3: 311 – 340.

van Dijk D., T. Teräsvirta and P.H. Franses (2002), Smooth transition autoregressive models – a survey of recent developments, *Econometric Reviews*, 21(1): 1 – 47.

Tables and Figures

Figures

Figure 1. GDP growth and recessions in Italy, 1970(I) – 2012(IV)

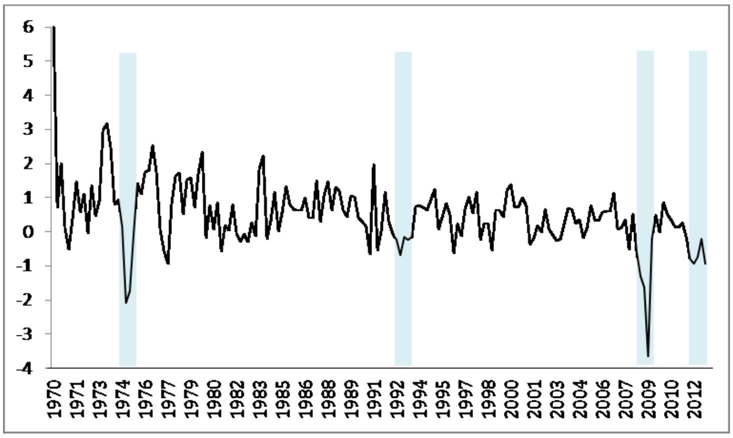
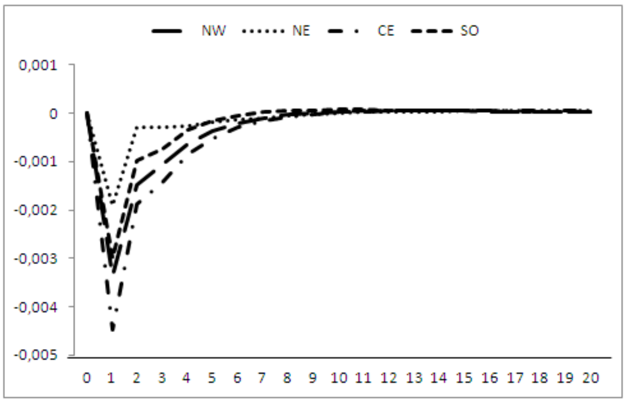
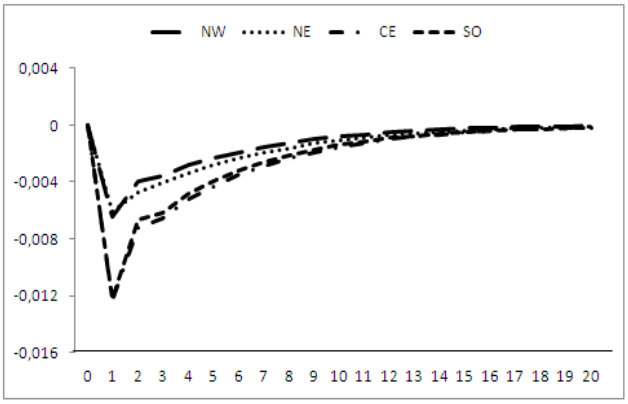


Figure 2. Impulse Responses: Italian recessions, 1977(I) – 2012(IV)

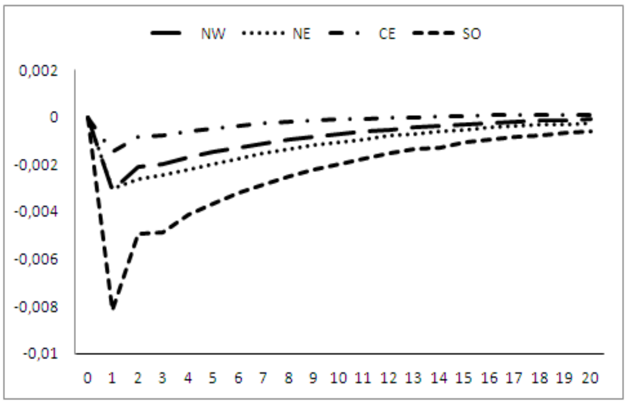
(a) Oil Shock



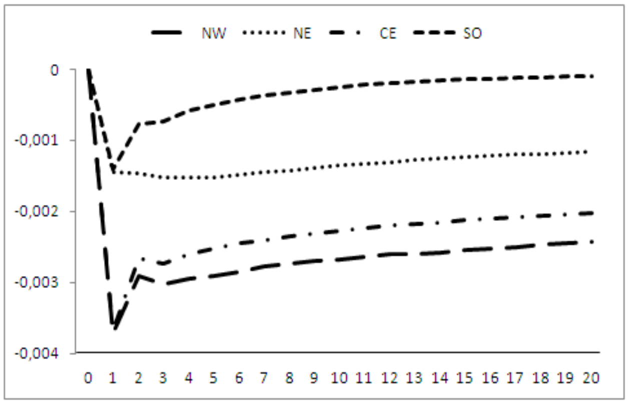
(b) Currency 'Lira' Crisis



(c) Financial Crisis

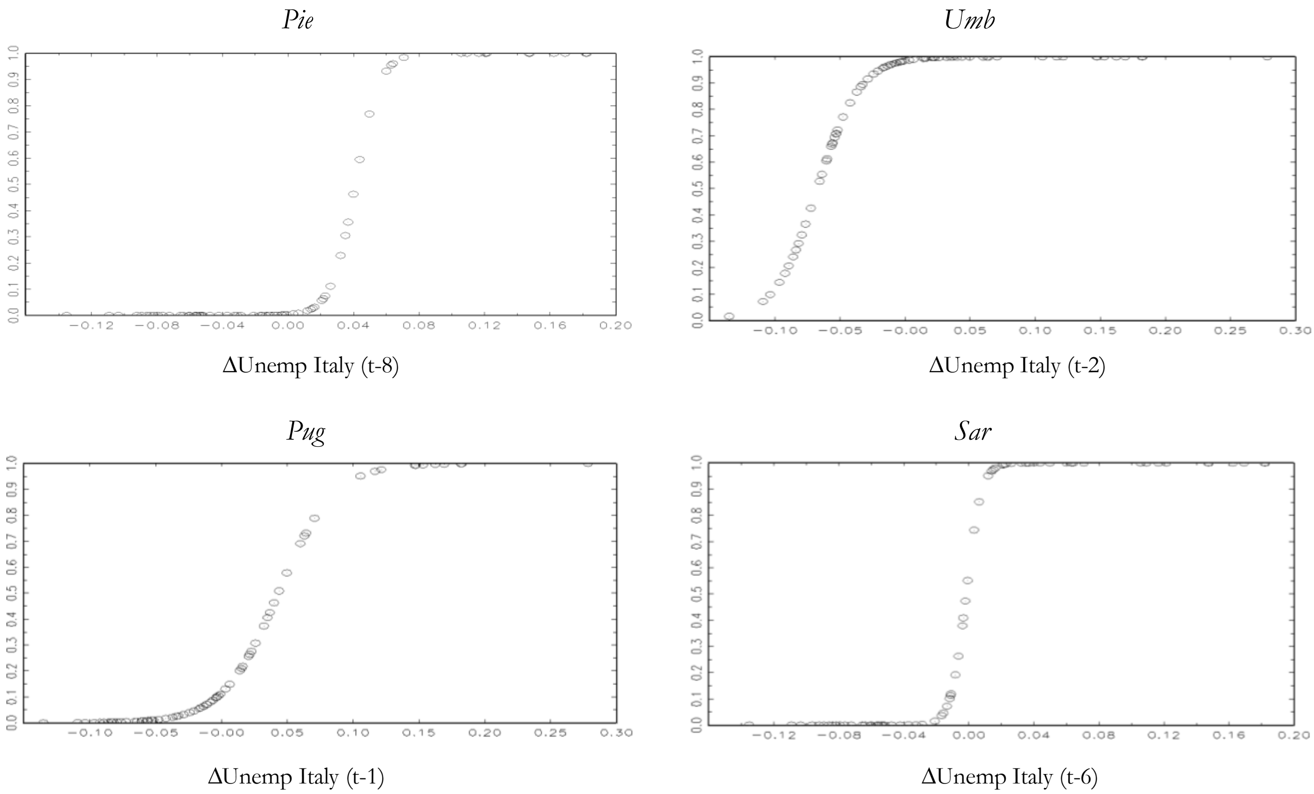


(d) Debt and Euro Crises



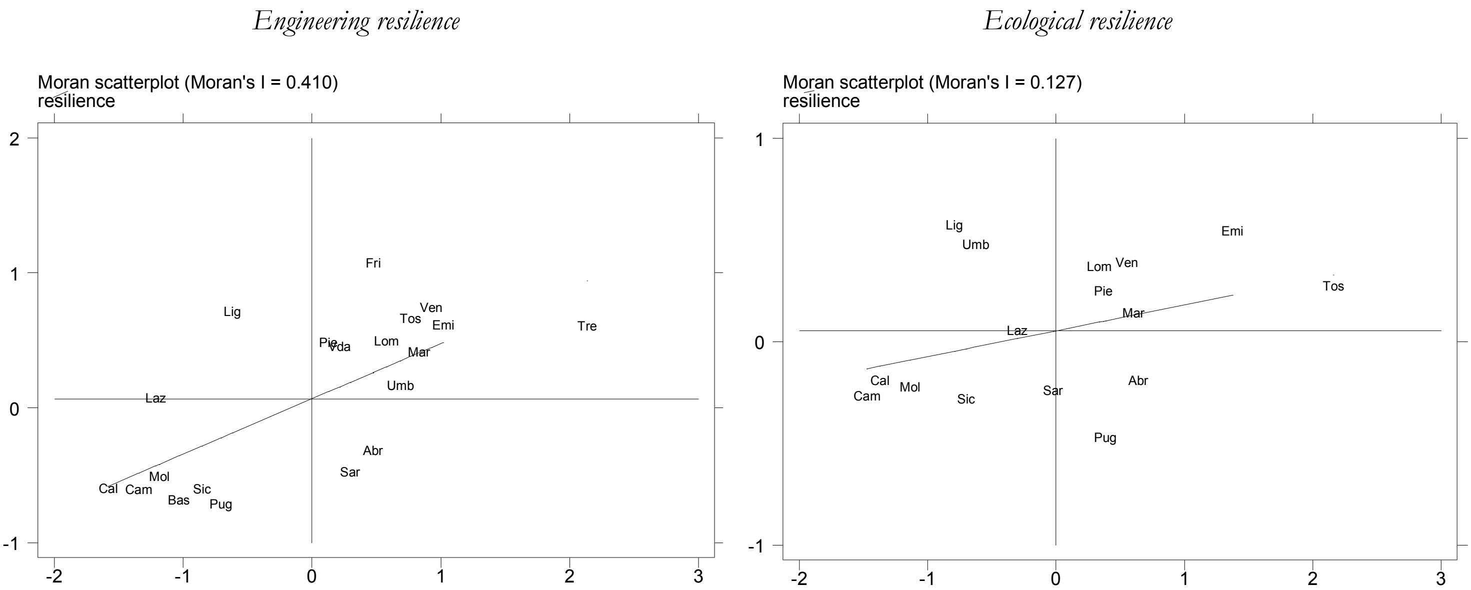
Note: Figure 2 (a-d) reports impulse responses (y axis) over periods 1-20 (x axis), for four Italian macro areas (North-West, North-East, Centre and South), obtained by estimating the model in (1).

Figure 3. Selected smooth transition functions



Note: Figure 3 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



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*	0.0808*	-	-	0.0145*	0.0175*	-	-
	(0.0459)	(0.0416)			(0.0094)	(0.0114)		
CIVIC	0.0143***	0.0129***	0.0112***	0.0097***	0.0164***	0.0124*	0.0159***	0.0125**
	(0.0037)	(0.0030)	(0.0031)	(0.0027)	(0.0021)	(0.0021)	(0.0017)	(0.0060)
FINANC		-0.0253*		-0.0240*		-0.0291*		-0.0287*
		(0.0173)		(0.0179)		(0.0188)		(0.0173)
MADEITALY			0.0156*	0.0147*			0.0158*	0.0146*
			(0.0112)	(0.0103)			(0.0114)	(0.0105)
Constant	0.4253	0.5995	-0.3012*	-0.2526	-0.1614	-0.2940	-0.2190	0.2012
	(0.4157)	(1.0005)	(0.1677)	(0.3965)	(0.2516)	(0.6603)	(0.0669)	(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*	0.0759*	0.0881*	0.0693*
	(0.0782)	(0.0467)	(0.0572)	(0.0465)
HUMCAP_ENTR		-22.90***		-26.08***
		(5.469)		(5.223)
Constant	-0.6635	0.1670	-0.3919	0.1833
	(0.5949)	(0.4051)	(0.8329)	(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 engineering resilience

(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

Table A1. 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 A2. 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 A2 (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 A3. 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.

I. Section II

I.A. Tests for nonstationarity

<u>Employment Italy</u>

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

<u>Employment North-West</u>

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

<u>Employment North-East</u>

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

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical 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

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical 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

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical 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

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical 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

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.586	-3.497	-2.887	-2.577

MacKinnon approximate p-value for Z(t) = 0.0060

I.B. 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

II. Section III

II.A. 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

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

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

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

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

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

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

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

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

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

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

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
Residual	5.1915e+09	79	65714672.9
Total	6.9706e+09	80	87131883.2

Number of obs =	80
F(1, 79) =	27.07
Prob > F =	0.0000
R-squared =	0.2552
Adj R-squared =	0.2458
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
Residual	410880192	79	5201015.09
Total	456319357	80	5703991.96

Number of obs =	80
F(1, 79) =	8.74
Prob > F =	0.0041
R-squared =	0.0996
Adj R-squared =	0.0882
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
Residual	9.8336e+10	79	1.2448e+09
Total	1.0791e+11	80	1.3489e+09

Number of obs =	80
F(1, 79) =	7.69
Prob > F =	0.0069
R-squared =	0.0887
Adj R-squared =	0.0772
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
Residual	2.9458e+10	79	372891477
Total	3.7242e+10	80	465520755

Number of obs =	80
F(1, 79) =	20.87
Prob > F =	0.0000
R-squared =	0.2090
Adj R-squared =	0.1990
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
Residual	1.9551e+09	79	24748701.2
Total	2.7054e+09	80	33817932.3

Number of obs =	80
F(1, 79) =	30.32
Prob > F =	0.0000
R-squared =	0.2773
Adj R-squared =	0.2682
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
Residual	2.7983e+10	79	354219485
Total	3.0980e+10	80	387255592

Number of obs =	80
F(1, 79) =	8.46
Prob > F =	0.0047
R-squared =	0.0967
Adj R-squared =	0.0853
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
Residual	3.7135e+10	79	470057286
Total	4.3867e+10	80	548335528

Number of obs =	80
F(1, 79) =	14.32
Prob > F =	0.0003
R-squared =	0.1535
Adj R-squared =	0.1428
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
Residual	1.1211e+10	79	141913621
Total	1.7640e+10	80	220506040

Number of obs =	80
F(1, 79) =	45.30
Prob > F =	0.0000
R-squared =	0.3645
Adj R-squared =	0.3564
Root MSE =	11913

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

II.B. 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 ($d = 8$).

II.C. 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%.