Regional recessions and recoveries in theory and practice: a resilience-based overview

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by

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Abstract

This paper surveys recent developments related to regional recessions and recoveries. Building on the idea of regional resilience, selected theoretical and empirical contributions are discussed in order to provide an overview of this area of research that looks at both equilibrium- and out-of-equilibrium approaches. On theoretical grounds, aggregate and disaggregate shocks are identified and separated, and hysteretic behaviours are examined. From an empirical perspective, linear and nonlinear econometric models are described and compared, with a particular focus on their spatial econometrics' extensions. Possible avenues of both theoretical and empirical future research are explicitly explored.

Keywords: regional evolution, hysteresis, aggregate shocks, disaggregate effects, spatial econometrics.

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

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1. Introduction

Three main reasons motivate the renewed interest for the study of regional recessions and recoveries in economics (see Francis *et al.*, 2013; Fingleton *et al.*, 2014): the presence of long-standing regularities like divergent patterns of convergence across territories and the rooted divide showed by different areas within the same country; the increased data availability at regional and municipal level experienced in recent times; the significant advancements achieved by specific empirical disciplines like spatial econometrics dealing with cross-sectional interdependences and neighbouring effects. From a policy perspective, moreover, the pivotal role of local reactions for solving global issues has been brought to the forefront of policy debate by both the OECD and the European Union (EU Inforegio, 2014) with the aim of overcoming the one-size-fits-all bias in growth strategies.

By refreshing the concept of economic resilience (see Reggiani 2002; and the special issue of the *Cambridge Journal of Regions, Economy and Society*, 2010), a conceptual framework can be considered for analysing the overall aspects of regional evolution. More specifically, the twin meaning of resilience, with 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), allows for a deep consideration of the uneven geography of booms and busts at a local level. Not surprisingly, then, an increasing number of contributions has progressively adopted this approach for looking at regional recessions and recoveries within and across different countries (see Fingleton *et al.*, 2012; Fingleton and Palombi, 2013; Cellini and Torrisi, 2014).

This survey aims to shed light on the theoretical and empirical advancements in the study of regional recessions and recoveries, by adopting a resilience-based perspective. The main objective is to propose a conceptual synthesis that is able to improve our understanding about regional evolutions and provide a picture of the state of the art on this topic. On theoretical grounds, the emphasis is posed on the distinction between temporary and permanent impacts of country-wide fluctuations: the former have been traditionally analysed by means of real business cycles models (King *et al*, 1998), while the latter through the length of multiple-equilibria specifications originally proposed by Kaldor and Myrdal. As for empirical contributions, with econometric works representing the bulk of this area of research, linear and non-linear econometric models that have been applied to this area are deeply discussed, with a particular focus on their recent spatial econometric extensions.

The remaining of the work is organized as follows. Section II presents the distinctive features of the regional resilience framework and why it can provide a helpful and original starting point for bridging the gap between alternative traditions in the analysis of regional evolutions. Theoretical contributions are surveyed in section III. Section IV deals with the recent developments in the empirical literature. The final section offers some concluding remarks and possible avenues for future research.

2. Resilience and regional evolution

The disaggregate effects of aggregate economic shocks have been historically analysed by making a distinction between the temporary and permanent impacts of country-wide recessions. One the one side, recessions have been modelled as temporary random fluctuations in the rate of technological change of a given economy in line with the real business cycles literature (Justiniano *et al.*, 2010): other things being equal, in the aftermath of productivity shocks, economies *lato* sensu (i.e. nations, regions, cities) bounce-back towards their previous levels of growth and employment. On the contrary side, a particular crisis may have permanent consequences on a local level, by sustaining hysteretic behaviours (Blanchard and Summers, 1986) and long-term jobless recoveries (Calvo *et al.*, 2013). The latter is associate to the idea that a given area does not necessarily evolve through self-adjusting dynamics, but it can be influenced by non-ideal relay (Göcke, 2002) and memory of recessions (Cross *et al.*, 2010).

In general, these contrasting views have resulted in two distinct strands of literature in regional economics, with the former representing the reference point for most of the theoretical works in this area, and the latter being of particular importance for economic geographers interested in evolutionary patterns across space (Boschma and Frenken, 2006) and alternative approaches (Setterfield, 2008). In the original formulation of Holling (1996), the concept of economic resilience, originating from other disciplines such as Engineering and Ecology, combined these two approaches, namely 'one that focuses on maintaining *efficiency* of function (engineering resilience) and one that focuses on maintaining *existence* of function (ecological resilience).' Put it differently, since its origin economic resilience has allowed for the consideration of these alternative paradigms in combination so as to provide a more complete analysis of the place-specific impact of country-wide disturbances (Simmie and Martin, 2010).

Engineering resilience is related to business cycles models assessing the transient impact of recessions and the characterizing elements of recoveries. As recently pointed out by Fatás and Mihov (2013), this way of analysing business cycles dates back at least to Mitchell (1927) and Burns and Mitchell (1946), and it has found an interesting application in the 'plucking' model of Milton Friedman (1964) and its extensions (Kim and Nelson, 1999). In this framework, recessions are extraordinary events which determines cycles, and there is a relation between a given recessionary event and its recovery. As a result, 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 (peak-reversion effect). The decline in GDP and employment does not influence an economy in a perpetual way, but regions and cities are involved in self-equilibrating continuous processes.

The notion of ecological resilience describes a situation where the adverse effects of crises become permanent not dying out over the periods. This view is close to the rooted idea of hysteresis in Economics, highlighting the persistence of specific disturbances influencing the path of an economy. The central element in this case is the relation between a given shock and the induced behaviour of the system under observation. A generic shock can either shift downward the long-run potential of a system while maintaining a constant rate of growth or it may cause a decline in the long-run growth as well as a variation over time perpetuating a perverse cumulative process. Alternatively, the recovery-phase after a recession can move the economy well above its initial equilibrium with a constant rate after a certain period, or it could stimulate positive reactions triggering a long-term favourable growth dynamic. Therefore, when looking at ecological resilience the main interest becomes the exact definition of the threshold of shock-absorption required to move from one equilibrium to another and the identification of which kind of equilibrium is achieved after a shock.

Having the idea of regional resilience in mind, the following pages review the advancements of theoretical and empirical contributions dealing with regional recessions and recoveries, by considering both the mainstream equilibrium approach and some of the most relevant disequilibrium-based specifications. 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, aiming at introducing multiple equilibria in unemployment (Farmer, 2013; Plotnikov, 2013). These models rely upon some assumptions peculiar to the 'Old Keynesian Economics' (Farmer, 2008), where the natural unemployment rate hypothesis does not hold and deviations of the unemployment rate from its optimal value may be permanent; they shall be distinguished from the second generation of real business cycles models where there are multiple patterns of adjustment for reaching the unique equilibrium level (Benhabib and Farmer, 1994).

3. Explaining regional evolution

The starting point of our analysis is a macroeconomic-based view of the disaggregate effects of aggregate variables which naturally leaves only a marginal role to the wide area of study developed by urban studies, economic geography and related disciplines. In what follows, moreover, a selective review is provided 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. A basic Real Business Cycle (RBC) model is firstly introduced and discussed, highlighting its main elements. 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 by providing some intuitions for its empirical application and possible avenues for future research. Finally, regional hysteresis is incorporated within the RBC framework, also discussing its origins and main consequences.

3.1 (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 background 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: 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, namely by overcoming the trend-cycle pattern. Thus, the discussion of traditional data-driven business cycle models is postponed to the empirical section.

The basic assumptions of the RBC approach 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; iv) the natural rate hypothesis holds for unemployment; v) agents have rational expectations and markets clear. For a more detailed discussion on the underlying assumptions, see Stadler (1994) and Farmer (2012). Let's consider[1] a representative individual living for an infinite time period and having preferences described by the relation:

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

where β^t, C_t, L_t denote the discount factor, consumption and leisure, respectively. Firms produce according to the following 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 the accumlation of capital 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, namely:

$$C_t + I_t \leq Y_t$$

$$N_t + L_t \leq 1.$$

[1] 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.

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

Individual preferences must respect the following restrictions: 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. Assuming that such restrictions hold and considering for simplicity that individual preferences are represented by a logarithmic utility function and production is expressed in the Cobb-Douglas form, the following system of equations allows for the determination of the time paths of output, consumption, capital, labour supply and total factor productivity:

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

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

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

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

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

Equations (1.1) – (1.5) represent: 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. In addition to these equations, 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. Note that total factor productivity follows a first order autoregressive process where the innovation has distribution $e_t \sim iid\ \mathcal{F}(0, \sigma^2)$. In this set up, 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).

Two main categories of disturbances are associated to the basic RBC specification.[2] Intuitively, 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. More relevantly, random fluctuations in the rate of technological change are able to hit the system under observation; only this second mechanism is defined as a recession in the RBC framework. Therefore, 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 sè*. Every shock represents a transitory fluctuations in economic activity away from a permanent level and the link between recessions and recoveries is generally missed when applying RBC models (Morley and Piger, 2012).

These general results still remain valid when additional features are introduced to the simple RBC framework. In particular, recent developments of Dynamic Stochastic General Equilibrium (DSGE) models have dealt with imperfect competition (Rotemberg and Woodford, 1995), taxes (Raurich *et al.*, 2006) and other frictions such as labour market rigidities (Smets and Wouters, 2007). Also, multiple steady-state adjustment patterns have been explored within the RBC framework (Behnabib and Farmer, 1994), which are derived from other driving forces than TFP shocks like increasing returns-to-scale.

The underlying structure of RBC models can be extended in principle to every economic system (i.e. country, region, city) without introducing *ad hoc* theoretical specifications: this has been the starting point of most of the empirical analyses studying economic shocks 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 elements of the model: for example, by introducing heterogeneity in the error terms or filtering the series for each region. Yet, most of RBC models do not allow to separate aggregate (i.e. national-wide) from disaggregate (i.e. place-specific) disturbances, and regional RBC applications can be flawed by the increased arbitrariness in setting the additional parameters in regionalised versions (Stiglitz, 2011).

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

3.2 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, 1996; Hamilton and Owyang, 2012). In general, disaggregate elements are considered as a by-product of aggregate cycles of which they represent a natural complement. To make a clear distinction between aggregate and disaggregate cycles, the simple prototype model presented by Danny Quah (1996) is discussed as its possible extensions. At a first glance, this model appears to be simple and naïve, as defined by Quah himself, but it is a flexible representation that is able to throw some light on the way regions react to national- and regional-specific shocks.

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 and its idiosyncratic features. In this sense, $z(x)$ is able to capture both time-invariant and time-varying regional elements.

Considering for simplicity 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, $f_l = \frac{\partial f}{\partial l} > 0$ denotes the productivity of labour, that is decreasing in l. Combining the production function in (1.6) with the measure π_x on locations, we can obtain a probability relation for the region-specific characteristics π_z, employment π_l and output π_y. Specifically, 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, as a result, 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, in equilibrium the following relations must hold

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

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

where $\bar{w}$ is the common wage at aggregate level. Quah (1996) has demonstrated that the maximization problem derived from this approach, namely

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

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

For exposure convenience and without loss of generality, 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 $\beta > 0$. The marginal productivity of labour results to be $w = f_l = \alpha l^{\alpha-1} z^\beta$, and local labour demand is $l = (\alpha/w)^{1/(1-\alpha)} z^{\beta/(1-\alpha)}$. Therefore, 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 each region the optimal allocation of employment is obtained by the relation

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

which positively depends on the 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:

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

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 $\bar{y} = \overline{w}/\alpha$.[3] Substituting this expression and the wage relation described in (1.13) into (1.15), and applying a logarithmic transformation, in equilibrium regional output becomes:

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

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

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

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 with respect 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. This was the way originally pursued in the Quah's contribution for capturing both distribution dynamics and the impact of a given shock. Causal relations between national aggregate series like country-wide GDP) and regional dynamics (i.e. shifts in the region-specific point distribution from one period to another) can be quite easily inferred in this set up.

3.3 Regional hysteresis

The specifications above have the merit of analysing the impact of shocks on the evolution of a given economic system in a quite robust way. 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 in a temporary way, without altering its underlying behaviour. In principle, the Quah's model could incorporate path-dependent effects by either 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 special cases.

Alternatively, one possible way of studying the persistent effects of economic shocks is the idea of hysteresis (Ball, 2009). Early contributions on this direction have been committed to find an explanation for the long-lasting dynamics encountered in some areas such as the high unemployment rate showed by specific European countries discussed in Blanchard (2006). 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. 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.

The decline in the stock of human and physical capital can perpetuate the long-lasting impact of recessions, due to the relation between capital shortage and unemployment, influenced by the inelasticity of factor substitution between labour and capital (Rowthorn, 1999; Stockhammer and Klaar, 2011). Insider-outsider effects in wage determination, labour hoarding and labour market tightness, firing costs and institutional rigidities are some of the additional reasons provided by the existing literature for explaining hysteresis (for a more detailed review, see Røed, 1997).

In order to investigate this pattern, let's consider a modified version of the RBC model presented in section 3.1, which is an adaptation obtained by using the assumptions of the 'Old-Keynesian Economics'. More precisely, this version of the RBC model allows for the presence of incomplete factor markets and the explicit introduction of the hypothesis that there are frictions in the labour supply curve (Plotnikov, 2013). The general assumptions of the basic RBC specification remain valid, implying that equations (1.1) - (1.3) and (1.5), and the three boundary conditions (i-iii, page 7) apply. What is different is the determination of the equilibrium wage, which in this case is obtained by a search mechanism, rather than in a competitive market. Now, equation (1.4) is divided in

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

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

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

As demonstrated 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, the recruiting technology, determined in aggregate and representing the degree of congestion in the labour market. As a result, 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

$$Z_t = (1 - \bar{L})^{1-\alpha}. \quad (1.19)$$

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. 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

$$C_t = \varphi Y_t^P, \quad (1.20)$$

where permanent income is given by the expression

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

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. Note that, since Y_t^P is a state variable, closing the model requires the following additional initial condition $Y_0^P = \bar{Y}^P$. For a more detailed discussion of the derivation of this model, see Plotnikov (2013).

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

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

$$\frac{\bar{Y}}{\bar{K}} = \frac{\rho + \delta}{\alpha}, \quad (1.23)$$

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

where the overscore characterizes variables at the steady state. Also, the following constraint must hold, $\varphi \equiv \frac{\rho + \delta(1-\alpha)}{\rho + \alpha}$.

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 valid for the basic RBC. Notably, this framework identifies the equilibrium employment at the steady-state as a path-dependent variable, which is driven by the adaptive expectations of the agents. 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/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 for the consideration of the long-term effect of exogenous shocks in terms of employment/unemployment. By linking the equilibrium level to expectations based upon future income and considering incomplete labour markets, the Plotnikov's model is able to relate unexpected disturbances to the persistent behaviour of unemployment. Being a quite novel approach in the macroeconomic literature, this 'Old-Keynesian' version of the RBC model needs further research. Nevertheless, its first empirical simulations provide supporting results and a possible starting point for extending the analysis at infra national level.

4. The empirics of regional recessions and recoveries

Since the seminal contribution of Burns and Mitchell (1946), the study of business cycles at both aggregate and disaggregate level has been primarily an empirical task. Macro econometricians have been deeply involved in dating, measuring, disaggregating and explaining the evolution of output series such as GDP or employment. In particular, the precise detection of turning points in economic activity and the reaction of a given economic system to unexpected disturbances have been challenging aspects faced by practitioners. For a more detailed discussion on the wide spectrum of techniques used in this area, see Stock and Watson (2003) and De Haan *et al.* (2008).

We select three main areas of empirical research focusing on regional recessions and recoveries. Firstly, the data-driven approaches are surveyed by exploring both well-established measures of economic activity like filters and leading indicators, and the bulk of this area of study, which is represented by the Markov-based perspective firstly pioneered by Hamilton (1989). Secondly, two structural linear models are presented, a structural VAR (SVAR) and a basic version of the regional dynamic latent factor model proposed by Owyang *et al.* (2009). Finally, nonlinear issues are addressed by introducing the Multiple-Regime Smooth-Transition Autoregressive Model (MRSTAR) discussed in van Dijk and Franses (1999). Spatial econometric extensions of the SVAR and the MRSTAR specification are carefully addressed in light with the more recent developments in these areas.

4.1. 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. Broadly speaking, this approach follows three main steps. The decomposition of the trend-cycle pattern in the series is initially made by means of non-parametric filters. Then, a measure of correlation is used for relating what is obtained from the previous step; at the end of this 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 results emerged from the data. In addition, one more step has been progressively developed, namely the estimation of the amplitude and the duration of recessionary events which allows for the quantification of the economic costs of different recessions (Claessens *et al.*, 2009; Fatas and Mihov, 2013).

The well-known Hodrick – Prescott high-pass filter is one of the most applied filtering approach. 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 us to separate cyclical fluctuations from trend dynamics, providing a first approximation of the incidence of disturbances on different economic systems.

Once the de-trended series have been obtained, the degree of business cycle synchronization across units and possible co-movements are investigate by measuring their 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 like the dynamic co-spectrum measure of Croux *et al.* (2001) and the concordance index of Harding and Pagan (2002). Of particular importance, the latter is able to capture co-movement by counting the percentage of the time where two economic series are in the same phase of the business cycle.

The natural next step is analysing what are the causes behind synchronization and co-movements. For instance, Belke and Hein (2006) have studied 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 to the original series of European regions. Going further, Artis *et al.* (2011) have extended this approach by introducing spatial effects in the second-step estimation through the application 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, Stock and Watson have defined a model relating the evolution of a given economy to an (unobserved) dynamic factor model represented by the following dynamic equations:

$$\Delta X_t = \alpha + \beta(\mathrm{L})\Delta c_t + \mu_t, \tag{1.25}$$

$$\gamma(\mathrm{L})\Delta c_t = \delta + \eta_t, \tag{1.26}$$

$$D(\mathrm{L})\mu_t = \epsilon_t, \tag{1.27}$$

where the system is composed by a measurement equation (1.25) and two transition equations (1.26) - (1.27). 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 adopted specification for measuring and dating recessions and recoveries is the Markov-switching model evolved along the lines tracing back to Hamilton (1989). Although this model is a nonlinear representation, it has been placed here and not in the subsection 4.3, given that it can be considered part of the data-driven approach. Here, business cycle turning points are linked to the mean growth rate of a parametric statistical time series model. Let's y_t identifies economic activity, a simple Markov-switching model results from the combination of the following relations:

$$y_t = \mu_{S_t} + \varepsilon_t, \tag{1.28}$$

$$\mu_{S_t} = \mu_0 + \mu_1 S_t, \tag{1.29}$$

with $\mu_1 < 0$ and $\varepsilon_t \sim N(0, \sigma^2)$ be the stochastic innovation. In a two-regimes context, the state variable $S_t = \{0,1\}$ captures the distinction between recessions and recoveries. Also, note that S_t is an unobserved variable and we need to specify its transition process. For instance, assuming that S_t follows a first-order two-state Markov chain, the 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 either in recession or expansion at a given point in time. The basic version of the Markov-switching model has been extensively modified and integrated. For a more detailed discussion on this area of research, see Chauvet and Yu (2006), Kim *et al.* (2008), Guerin and Marcellino (2013).

At a regional level, this procedure has been applied with some success for investigating the time of entry and exit of each State in the US during different national-wide recessions (Owyang *et al.*, 2005). 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 the US States in different clusters with similar business cycle characteristics. Using Bayesian posterior inference, the authors have provided additional evidences on the geographical unevenness of recession in the US. The appropriateness of this model for forecasting purposes at disaggregate level has been recently addressed by Owyang *et al.* (2012). In this contribution, the authors have combined aggregate and disaggregate predictors in a probit model that has been 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.

The data-driven approach 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. Further explorations, however, are needed for assessing the validity of this approach, and in particular, of the Markov-switching modelling, for making feasible forecasts on the disaggregate effects of economic shocks.

4.2. Structural linear models

Clark (1998) provides one of the first application of the structural linear vector autoregression (SVAR) modelling for disentangling national-, regional- and industry-specific employment fluctuations. This specification was applied for analysing the evolution of employment across the US case over the period 1947 - 1990. Using matrix notation, the original Clark's model assumes the following form:

$$\mathbf{Y}_t = \sum_{j=1}^{J} \mathbf{\Gamma}_j \, \mathbf{Y}_{t-j} + \mathbf{e}_t, \tag{1.30}$$

$$e_{r,t} = \gamma_r c_t + \sum_i \tilde{\alpha}_{r,i} \mu_{i,t} + u_{r,t}, \tag{1.31}$$

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

where $\mathbf{Y}_t$ is the $(R + I) \times 1$ vector of region and industry employment growth rates, $\mathbf{\Gamma}_j$ the coefficient matrix to be estimated and $\mathbf{e}_t$ the vector of error terms. Equations (1.31) - (1.32) 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.

As for the identification process of this model, the coefficient γ that captures the impact of the common national shock has to be estimated, while the parameters $\tilde{\alpha}_{r,i}$ and $\tilde{\beta}_{r,i}$ are constant values. In the original formulation, the coefficient $\tilde{\alpha}_{r,i}$, which represents the industry-specific shock on each region is set equal to the employment share of industry i in region r's total employment; the coefficient $\tilde{\beta}_{r,i}$, 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 for the introduction of a distinct source of country-wide fluctuation and two related disturbances arising from regions and industries. To complete the identification of the model, Clark applied 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 former 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 technique 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 this approach for analysing recessions and recoveries on a regional level can appear a worthwhile task: in this sense, see the contribution of Carlino and De Fina (1998), which apply the SVAR framework to identify disaggregate responses to aggregate shocks across the US.

Yet, modelling spatial interdependencies and a significant number of units within the SVAR framework means amplifying the over-parameterization problem traditionally associated to these specifications. This issue has been recently the focus of some promising research contributions in the econometric literature. In a set of papers (Lastrapes, 2005 and 2006), the over-parameterization bias of the basic SVAR has been solved by introducing some explicit specifications leading to a large-scale SVAR. More specifically, the proposed large-scale SVAR can be represented as follows:

$$A_0 z_t = A_1 z_{t-1} + \cdots + A_p z_{t-p} + u_t \tag{1.33}$$

where $A_0, \dots, A_p$ are $n \times n$ structural parameters matrices, $z_t = \begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix}$ is a partition of the generic endogenous vector z_t, with z_{1t} be a $n_1 \times 1$ set of aggregate or common variables, z_{2t} a $n_2 \times 1$ set of disaggregate or state-level variables and $n_1 + n_2 = n$. $u_t = \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$ denotes the set of white noise uncorrelated errors which is assumed to be normalized. The reduced VAR representation of the structural model in (1.33) is:

$$z_t = B_1 z_{t-1} + \cdots + B_p z_{t-p} + \epsilon_t \tag{1.34}$$

with $B_1 = {A_0}^{-1} A_1, B_p = {A_0}^{-1} A_p, \epsilon_t = {A_0}^{-1} u_t$ and $E(\epsilon_t {\epsilon_t}') \equiv \Omega$.

The identification of this model requires two restrictions: i) aggregate variables are determined independently by the state-level variables, namely z_{1t} is block-exogenous with respect to z_{2t}; ii) country-specific variables in z_{2t} are jointly independent, with the exclusion of possible neighbouring effects, after conditioning on z_{1t}. Once the model has been identified, it can be estimated by adopting a two-step procedure, imposing a specific Cholesky decomposition of the covariance matrix, and applying the seemingly unrelated regression (SUR) estimator (Beckworth, 2010). The large-scale SVAR is able to quantify the disaggregate reactions to unique common shocks, resulting very important for policy implications.

Building on Spatial Econometrics, in a pioneering contribution, Valter di Giacinto (2003) has solved the over-parameterization of the basic SVAR by developing a spatial version of the SVAR model (SpVAR),[4] which explicitly considers simultaneous regional interdependencies across geographical areas. The idea behind the SpVAR model is the assumption that the impact of region-specific shocks is linked across units by neighbouring effects and it progressively decreases as geographical distance increases. The author maintains the three assumptions of the original formulation of Carlino and De Fina (1998): i) region-specific shocks contemporaneously affect only the region of origin, though they can spill over into other regions during future periods; ii) aggregate shocks are assumed to

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

affect regional variables with least a one-period time lag; iii) macro control variables are not contemporaneously affected by shocks in the remaining variables in the model and they do not affect each other.

In addition, two further constraints are required for the identification of the SpVAR model: i) standard (non-spatial) constraints are linked to the recursive ordering of the endogenous variables; ii) the restrictions on the spatial effects coefficients are derived from the underlying spatial structure captured by spatial weight matrices that capture geographical proximity. Once it has been identified, the SpVAR can be estimated by applying Full Information Maximum Likelihood (Amisano and Giannini, 1997). For a more detailed discussion and an empirical application, see Di Giacinto (2010). In this set up, estimation results can be interpreted by means of space time impulse response (STIRs) functions (Di Giacinto, 2006), which are able to detect state-specific economic responses to a common macro shock.

Another way of looking at regional evolutions is based upon the dynamic-factor model as initially generalized in Forni *et al.* (2000). Here, the regional extension of the dynamic-factor model presented in Owyang *et al.* (2009) is briefly discussed. Let's consider the following relation:

$$X_{i,t} = \lambda'_i F_t + e_{i,t}, \tag{1.35}$$

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 (1.35) is the application of 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), the basic dynamic-factor model has been integrated with a Markov-switching structure of the common component. Apart from the theoretical results achieved by means of these extensions, 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 modelling the dynamic common factor in an appropriate way.

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

$$\lambda'^{\,j}_{i} = \rho W \lambda'^{\,1}_{i} + A\beta_0 + Z\beta_1 + WZ\beta_2 + v, \qquad (1.36)$$

where $\lambda'^{\,j}_{i}$ is the vector of estimated factor loadings affecting region i, W is the spatial weight matrix well-known to Spatial Econometricians, 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 are obtained by applying Maximum likelihood. A more articulated version of the spatial generalized dynamic-factor model has been proposed in Lopes *et al.* (2011).

Structural linear models are widely applied in the empirical literature given their ability to deal with macroeconomic data. Their application at a regional level provides a fruitful area of research, though further contributions will be welcomed especially for introducing more robust spatial interactions. The forecasting performance of these models is an open question in the literature as discussed in Chauvet and Potter (2012): whether their in-sample forecasting ability seems quite affordable, the out-sample one shows some limitations. In general, the SVAR models are good predictors in normal times, but during recessions they do not provide accurate forecasts, while the dynamic-factor models do quite well in forecasting during recessions (see, among others, Stock and Watson, 2003; Marcellino *et al.,* 2003).

4.3. Nonlinear developments

Yet in his 1951 *Econometrica* paper, Richard M. Goodwin explored the non-linear behaviour of the business cycle in search of a different explanation for the underlying structure of a given economy. Whether national and regional dynamics are better approximated by a non-linear dynamic instead of a linear one is an open debate within the theoretical and empirical econometric literature studying recessions and recoveries (Potter, 2012; Morley *et al.*, 2012). The Markov-switching autoregressive model yet discussed, 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). In general, the introduction of nonlinear attributes is welcomed given that it contributes to model multiple equilibria, asymmetric adjustments and path-dependent patterns.

Our focus is posed on the multiple-regime smooth-transition autoregressive (MRSTAR) model firstly presented by van Dijk and Franses (1999) and recently discussed in Hubrish and Terasvirta (2013). Two main reasons motivate the adoption of this particular specification, namely its ability to take into account multiple regimes and the attribution of a particular informative content to the transition(s) variable(s) which will be explained below. For a univariate time series y_t, a general representation of the four-regime MRSTAR model is:

$$\begin{aligned} y_t = &\left\{\phi_1' y_t^{(p)}\left(1 - G_1(s_{1t};\gamma_1, c_1)\right) + \phi_2' y_t^{(p)} G_1(s_{1t};\gamma_1, c_1)\right\} \times [1 - G_2(s_{2t};\gamma_2, c_2)] \\ &+ \left\{\phi_3' y_t^{(p)}\left(1 - G_1(s_{1t};\gamma_1, c_1)\right) + \phi_4' y_t^{(p)} G_1(s_{1t};\gamma_1, c_1)\right\} \\ &\times [G_2(s_{2t};\gamma_2, c_2)] + \varepsilon_t, \end{aligned} \tag{1.37}$$

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 transition function $G_j(s_t;\gamma, c)$, with $j = 1,2$, is continuous and bounded between 0 and 1, and, without loss of generality here we prefer to use the logistic version (LSTAR):

$$G_j\left(s_{jt};\gamma_j, c_j\right) = \left\{1 + exp\left[-\gamma \prod_{k=1}^{N}(s_{jt} - c_{jk})\right]\right\}^{-1}, \qquad \gamma > 0 \tag{1.38}$$

with γ_j denoting the speed of transition between regimes, 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. Three features of the parameter γ are worth noting: i) $\gamma > 0$ is an identifying restriction; ii) when $\gamma \to 0$ the model in (1.38) becomes linear; iii) when $\gamma \rightarrow \infty$ the logistic function approaches a Heaviside function, having the value 0 for $s_t < c$ and 1 for $s_t > c$.

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 allows for the consideration of 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. Notably, the MRSTAR specification nests several other non-linear time series models.

The model obtained by combining (1.37) and (1.38) 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 in this framework is the choice of the combination of the two transition variables s_{1t} and s_{2t}, which determines 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 either 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 the latter point, 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). As a consequence, 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. Put it differently, 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. Specifically, six steps shall be sequentially carried out: a) specify a linear *AR(p)* model for the dependent variable under analysis; b) test the null hypothesis of linearity against the alternative of nonlinear LSTAR; c) if linearity is rejected, define the appropriate transition function and estimate the nonlinear LSTAR model; d) test 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, estimate the MRSTAR model by conditional maximum likelihood (or nonlinear least squares); e) conduct post estimation robustness checks. The LM test for discriminating between the presence of two *vs* multiple regimes (point d above) derives from 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 economic interpretations arising from this model.

Some recent works (Pedé *et al.*, 2009; Lambert *et al.*, 2012) have addressed the possibility of estimating spatial versions of the LSTAR model, by incorporating spatial interactions in the Taylor-approximation of the transition function. Specifically, these authors modify the transition function so as to introduce neighbouring effects across units. Therefore, the LSTAR function in (1.38), now becomes

$$G_j\left(Wy_{jt};\gamma_j,c_j\right)=\left\{1+exp\left[-\gamma\prod_{k=1}^{N}(Wy_{jt}-c_{jk})\right]\right\}^{-1},\qquad \gamma>0 \qquad (1.38)$$

with Wy_{jt} be the transition function incorporating spatial effects through the spatial weight matrix W. Also, the authors develop several tests for detecting the presence on nonlinearities and apply Monte Carlo simulations to assess their robustness. Then, they apply this spatial version of the STAR model to estimate economic growth across the US States, achieving interesting results. In principle, this extension can be valid also for the MRSTAR specification previously discussed. Further research, however, is required in order to make this approach more feasible to practitioners.

The accuracy of non-linear specifications for forecasting purposes is a vivid area of debate among macro econometricians (Teräsvirta, 2006; Ferrara *et al.*, 2013). Notably, two aspects have been recognised: as suggested by Stock and Watson (1999), the comparison between different nonlinear models shall be a performed when looking at forecasts; 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. For a more detailed treatment, see Lin and Granger (1994).

5. Conclusion

In this paper we have developed a critical survey of some of the most prominent theoretical and empirical works looking at regional recessions and recoveries. Selected areas of research have been reviewed with the aim of providing a well-equipped and original roadmap for professional economists and practitioners interested in these topics. To this end, the starting point has been the regional resilience framework, recently moved to the forefront in regional economics and economic geography, which allows for the contemporaneous treatment of equilibrium- and out-of-equilibrium-based approaches. In doing this, we have been able to present a somewhat all-embracing and updated picture of regional evolution, at least from a macroeconomic perspective. Moreover, recent advancements in the empirical literature have been carefully addressed, with a particular emphasis posed on spatial econometric developments. Next years will probably continue to be characterized by a separation, in theory and in practice, between equilibrium and disequilibrium models dealing with regional recessions and recoveries. However, the ideas derived from the Old-Keynesian's adaptation of the basic RBC specification and the renewed interest in making more affordable comparisons among nonlinear and linear econometric models will act in favour of maintaining a broader view when analysing regional evolutions.

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