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WHY SHOULD REGIONAL AGRICULTURAL PRODUCTIVITY GROWTH CONVERGE?

Evidence from Italian Regions

ROBERTO ESPOSTI

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Roberto Esposti[§]

Abstract

The paper analyses agricultural TFP growth across Italian regions during the 1952-2002 period, and aims at identifying those factors that favour or hinder regional agricultural TFP growth convergence. Among them, idiosyncratic, R&D-spillover and learning components are included. Of major relevance is whether regions, despite their inescapable heterogeneity, tend to share common technological improvements, that is, to move along the same productivity growth rate. TFP growth decomposition ultimately allows attributing observed productivity performance to convergence and divergence forces. Appropriate testing and estimation procedures are adopted to take into account panel unit-root issues and cross-sectional dependence.

Keywords: TFP growth, Convergence, Spillover, Panel Data, Unit Root
EconLit Classification: Q100, Q160, O130, O180

[§] Department of Economics, Università Politecnica delle Marche (Ancona – Italy), Piazza Martelli, 8 - 60121 Ancona – Italy, Tel. +39 071 2207119, Fax +39 071 2207102, r.esposti@univpm.it, www.dea.unian.it/esposti.

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Contents

1. Introduction

Productivity comparison across sectors, countries or regions represents one of the challenging and critical topics in growth empirics (Acemoglou and Zilibotti, 2001; Durlauf et al., 2005). On the one hand, many growth models, and many growth exercises as well, assume equal long-run Total Factor Productivity (TFP) growth across observations (Temple, 1999). Therefore, it is of major interest to assess whether this assumption finds empirical support. Secondly, since Solow (1957) first seminal contribution, it has become evident that TFP growth, rather than factor accumulation, often constitutes the main growth driver (Wong, 2007), as well as the major responsible of long-term growth differences and conditional growth convergence (Easterley and Levine, 2001; Wong, 2007).

The basic idea underlying these models, and empirical results, is that the adoption of the same technologies may lead countries, regions and sectors along the same growth pattern. When referred to the specific case of agricultural production, this notion evidently magnifies its interest especially for the key role this sector assumes in early stages of economic development. Several empirical contributions investigated agricultural productivity differences across countries (Ball et al., 1996; Craig et al, 1998; Ball et al., 2001; Martin and Mitra, 2001; Ball and Norton, 2002) and also attempted to explain why these differences may permanently occur (Schimmelpfenning and Thirtle, 1999; McCunn and Huffmann, 2000).

Factors acting in favour of convergent agricultural productivity performance may be particularly appreciated among relatively similar production contexts (Ball and Norton, 2002). This paper therefore analyses agricultural TFP growth across Italian regions aiming at identifying those forces eventually promoting or impeding TFP growth convergence. Italian agriculture productivity growth has been investigated in a series of contributions (Pierani and Rizzi, 2005; Esposti and Pierani, 2000, 2006b) also paying attention to its major drivers (Esposti and Pierani, 2003, 2006a; Maietta, 2004). More recently, emphasis have been put also on regional differences in this respect (Pierani, 1989; Maietta and Viganò, 1995; Pierani and Rizzi, 2005; Rizzi and Pierani, 2006; Brasili et al., 2007; Pecci and Sassi, 2007).

In particular, empirical investigation here concerns whether regions, despite their inescapable heterogeneity, tend to share the same long-term productivity growth rate. Consequently, the TFP growth convergence hypothesis, rather than more conventional TFP level convergence (Harrigan, 1997; McCunn and Huffmann, 2000), is here under consideration.

2. Driving forces of TFP growth: a short overview

Technological progress (hence, TFP growth) can be the result of either intended or unintended decisions of economic agents. Analogously, technological progress may be either strictly confined into a single farm (or firm), sector, country or region (*internal effects*), or freely extend to a large set of other contexts (*external effects*) (Keilbach, 2001). Theoretical as well as empirical literature has often interpreted intended technological change as aimed at generating internal effects, whereas external effects are usually represented as unintended consequences (Backus et al., 1992).

For a given unit of observation (a farm/firm, a country, a region), first internal and intended effects concern productivity improvements resulting from own R&D effort (formal or informal). In addition, internal, but often unintended, cumulative processes also generate productivity growth usually as consequence of learning (learning-by-doing, by-using or accumulation of skillness and human capital) (Backus et al., 1992) whose eventual outcome, in practice, is that TFP grows as output or scale of production increases, at either the farm or aggregate level (Caniëls, 2000).

Moreover, productivity performance at the individual (disaggregated) level may show an idiosyncratic, permanent as well as short-term or cyclical, behaviour attributable to own capacity or attitudes but also to those non permanent technological or non-technological shocks typically affecting TFP measure (Slade, 1988; Esposti, 2000a). Mentioned factors restrict their effect on TFP within the unit of observation (namely, the region in the present case). Consequently, whenever these factors operate with different magnitude across units, different TFP growth rates are going to be observed and, if persistent in the long-run, they will imply diverging TFP levels (*diverging forces*).

Other forces, however, operate outside the limits of any specific unit. Firstly, public R&D investments, by definition, should aim at fostering TFP growth across all units (though not necessarily with the same magnitude). Secondly, effects generated within any single unit can diffuse over other units. Depending on which units are under observations, these spillover effects can alternatively take the form of across-firm(farm), intersectoral, international or interregional spillovers (Coe and Helpman, 1995; Madsen, 2007; Park, 2004; Añón Higón, 2007). In any case, these two external forces eventually tend to equalize TFP growth rates across units and, if persistent in the long run, to make TFP levels converge (*convergence forces*). Table 1 summarizes these divergence and convergence forces.

At the regional level, opposition of external (spillovers) and internal (agglomeration economies) effects is one of the key theoretical and empirical research issue (Caniëls, 2000; Keilbach, 2001). Agriculture, in particular, presents some specific characters in this respect (last column of Table 1). On the one hand, R&D effort is mostly made by public institutions so it expected to generate public knowledge and largely accessible innovations as an intended effect (Huffmann and Just, 1999). On the other hand, however, if we consider regional agricultures as units of observation, we should distinguish between R&D largely available and accessible to all regions, and whose results can be indifferently adopted in all cases, from that part of public R&D which is actually strongly region-specific, thus whose results are not transferable to other regions being focused on quite specific characters (products, structures, markets) of regional agricultures.[1]

In this specific case, spillover effects can be relevant across sectors of the same regions, particularly from non-agricultural industries to agriculture, but weak across regions. Consequently, both public R&D and spillovers may indeed generate either convergence or divergence forces across regions, depending on how their impact is distributed between intraregional and interregional effects. This specific dimension of agricultural productivity growth and its causes has been substantially disregarded in empirical literature. Although many papers analyse how public agricultural R&D (Alston and Pardey, 2001; Ball and Norton, 2002) and spillovers (Schimmelpfenning and Thritle, 1999; Esposti, 2002; Gutierrez and Gutierrez, 2003) affect agricultural TFP, not much has been done in understanding whether these effects actually facilitate TFP growth levelling across units of observation.

3. The model

We consider, as units of observation, *N* regional agricultural sectors observed over *T* years. Following a widely used representation (Bakus et al., 1992; Hall, 2006; Sterlacchini and Venturini, 2007), we represent the i-th regional agriculture ($\forall i = 1,\ldots,N$) at time t ($\forall t = 1,\ldots,T$) with an augmented Cobb-Douglas production function:

(1) $Y_{it} = (\gamma_{it} S_{it}) L_{it}^{\alpha} K_{it}^{1-\alpha} \left(R_{it}^{\beta}\right)$

where Y_{it} is agricultural output, L_{it} and K_{it} are the conventional agricultural labour and capital inputs, respectively;[2] for these conventional factors of production, constant returns to scale are assumed. Non conventional production factors are in square brackets: R_{it} indicates

[1] This distinction is evidently not trivial, in practice, and somehow arbitrary. At this stage of the analysis, however, it aims at conceptualizing the issue. Presentation of the empirical model in next section clarifies the point.

[2] K aggregates also agricultural land and materials (see Rizzi and Pierani, 2006, for details).

the R&D input (R&D stock), while $(\gamma_{it} S_{it}) = A_{it}$ is the standard disembodied productivity here represented as a combination of an exogenous component (γ_{it}) and a scale (namely, learning as clarified below) effect (S_{it}).

Taking logarithms and totally differentiating (1),[3] we obtain the conventional non-parametric measure of TFP growth, or Solow residual[4]:

(2) $\dot{TFP}_{it} = \dot{Y}_{it} - \alpha \dot{L}_{it} - (1-\alpha)\dot{K}_{it} = \dot{\gamma}_{it} + \dot{S}_{it} + \beta \dot{R}_{it}$

In (2), TFP growth depends on the combination of three effects ($\dot{\gamma}_{it}$, $\dot{S}_{it}$, $\dot{R}_{it}$). After adding an autoregressive (AR(1)) term, we can detail them (and $\dot{R}_{it}$, in particular) further into the following 7 components (Table 2):

1. *AR(1) component*: $\rho \dot{TFP}_{it-1}$. It is a term representing the short-term persistence or cyclical behaviour (expressed by parameter ρ) often observed in TFP growth rates (Slade, 1988; Esposti, 2000a).

2. *Idiosyncratic permanent component*: $\gamma_{it} = e^{\lambda_i t}$ therefore $\dot{\gamma}_{it} = \lambda_i$, it is the standard exogenous disembodied technical change proxied by a time trend.

3. *Learning component*: $\dot{S}_{it} = \ln \tilde{\beta}_i + \tilde{\varphi}\,\dot{Y}_{it}$. It is the scale effect generally expressed by the direct relation existing between output growth and productivity growth and often

3 For a generic variable x_{it}, $\dot{x}_{it} = \frac{\partial \ln x_{it}}{\partial t}$.

4 This conventional index-number TFP calculation implies constant returns to scale with respect to conventional inputs, as assumed above (Rizzi and Pierani, 2006). If non-constant returns to scale occur, TFP calculation may still take into account scale effects (Pierani and Rizzi, 2005). Here, however, these are already captured in the scale (learning) term S_{it}. In practice, scale effects generated by learning and those resulting from other non-technological factors are not distinguishable; thus, learning may be overestimated when TFP is computed assuming constant returns to scale. It must be also reminded that this TFP growth calculation also assumes Hicks-neutral technical change and perfect competitive markets for output and conventional inputs. These latter assumptions, however, do not seem to have major implications for the interpretation of results.

associated to learning processes (thus, here identified as "learning component", for simplicity). In fact, starting with the original formulation by Arrow (1962), learning[5] has been modelled as a scale effect with major long-term growth implications. Backus et al. (1992) model this effect as $S_{it} = S_{it-1}\left(1+\beta_i Y_{it}\right)^{\varphi_i}$, thus $\dot{S}_{it} \cong \ln\beta_i + \varphi_i \ln Y_{it}$ whenever $\left(1+\beta_i Y_{it}\right) \cong \left(\beta_i Y_{it}\right)$ (see also Matsuyama, 1992 p.320), but it may also assume more complex functional forms (Randon and Naimzada, 2006). In their empirical studies on agricultural TFP growth, Govindan et al. (1996) and Gopinath and Roe (1997) refer to this specification. Nonetheless, it should be noticed that such representation, when applied to geographical units (countries or regions), makes TFP growth depend on geographical dimension (through Y_{it}), as it is an increasing function of output (though showing diminishing returns). It seems more realistic and suitable, in such cases, to return to the original notion, that is, to assume *TFP growth be an increasing function of output growth* in the form $\dot{S}_{it} \cong \ln\tilde{\beta}_i + \tilde{\varphi}\,\dot{Y}_{it}$, where $\ln\tilde{\beta}_i$ and $\tilde{\varphi}_i = \tilde{\varphi}, \forall i$ are unknown region-specific and region-invariant parameters, respectively (Caniëls, 2000; Keilbach, 2001; Backus et al., 1992, p.382).[6] In fact, Govindan et al. (1996) and Gopinath and Roe (1997) eventually use this latter specification in estimating the causes of agricultural TFP growth.[7]

[5] Alternatively assuming the form of learning curve, learning-by-doing, learning-by-using.

[6] It is worth noticing that representing TFP growth as an increasing function of cumulative output growth is not exclusive of neoclassical growth models. In fact, it can be found in other approaches and often indicated as the *Verdoorn-Kaldor Law*.

[7] The choice between these two alternative formulations of learning has been somehow an issue since the original Arrow formulation of learning by doing. The problem is whether the scale effect implied by learning (TFP increasing with output) has a permanent effect on TFP growth or not. Although an appropriate definition of respective parameters may generate the same TFP pattern in the two cases, in fact, growth implications (in particular, in terms of endogenized growth rates and generation of increasing returns) of these alternative representations are extremely relevant (Backus et al., 1992). Eventually, the former case tends to induce dramatic growth, whereas in the latter, TFP growth tends to be decreasing with respect to a given increase of output. It should be also noticed that learning is sometimes also modelled relating TFP growth (or cost reduction) to cumulative investments (the original Arrow formulation); the use of cumulative output, however, has become prevalent (Randon and Naimzada, 2006).

4. *Intraregional intersectoral spillover*: $\beta\phi \dot{R}_{Eit}$. This term represents that part (ϕ) of other sector's R&D spilling in regional agriculture within the same region. β is the Cobb-Douglas parameter of R&D and indicates its impact (elasticity) on TFP.[8]

5. *Public agricultural R&D*: $\beta\delta \dot{R}_{At} + \beta\chi_i \dot{R}_{At}$. Entering public agricultural research in (2) is problematic for two major reasons. Firstly, we only have data on the aggregate public agricultural R&D expenditure observed at the national level, R_{At}.[9] It includes both the regional and the country-level research activities, but the latter can either deliver their effect across all regions or be strongly region-specific. Secondly, even if we had statistical information on region-by-region R&D expenditure, nonetheless this would not correspond to the actual R&D input any region can exploit, as research done in one region can (and usually does) spill into other regions, especially the closer ones in geographical and economic terms. We can try, however, to partition R_{At} in two components. The first component (5a) concerns the region-specific and rival expenditure, thus corresponding to N different shares on total

8 In proxing and measuring spillovers, the role of further variables could be also recognized. In particular, it is widely acknowledged, in both theoretical and empirical literature, that some characteristics of the recipient region (or sector) may increase the spillover effect because they increase the "absorption capacity" for new knowledge or technology (Cohen and Levinthal, 1989). Human capital probably is the most important factor affecting this absorption capacity (Abreu et al., 2004). In the case of agriculture, expenditure in extension services and, more generally, in technological information, may be critical, as well (Esposti and Pierani, 2000). As mentioned, human capital might be also considered a determinant of the degree of learning, that is, of parameter $\tilde{\varphi}$ in $\dot{S}_{it} = \ln\tilde{\beta}_i + \tilde{\varphi}\,\dot{Y}_{it}$. Here, however, we do not explicitly include these further variables in the empirical model. The major argument for this is the lack of appropriate regional data over the whole period under question. Conventional regional proxies for agricultural human capital can be, in fact, computed (Maietta, 2004). Nonetheless, the combination of schooling, skillness and experience forming human capital is, within the somehow unique characteristics of agricultural labour force, particularly complex and also strongly changes over time (Maietta, 2004). For these reasons, measuring human capital as in other sectors may incur misleading interpretations in agriculture while, unfortunately, more sophisticated and specific measures or indicators of agricultural human capital are lacking. It should be also taken in mind that, explicitly accounting for human capital, would also imply to explicitly consider its flow across regions and sectors implied by migration. In the early decades of the period under study, migration across regions and sectors (mainly from South to North and from agriculture to other sectors) has been particularly intense, but appropriate data on such interregional flows are lacking, as well. Nevertheless, improvements in these directions could be suggested in future research.

9 As clarified below, R_{At} actually indicates the aggregate (national) public agricultural R&D stock.

(national) expenditure; the second (5b) is the common (nation-wide) and non-rival part and equally applies to all regions. We can thus write: $\dot{R}_{At} = \sum_{i=1}^{N} \chi_i \dot{R}_{At} + \delta \dot{R}_{At}$, $\forall i = 1,...,N$, where χ_i parameters indicate the region-specific shares of public R&D, while δ indicates the non-rival R&D component. It follows that $\dot{R}_{it} = \delta \dot{R}_{At} + \chi_i \dot{R}_{At}$. Evidently, the following relation must hold: $\sum_{i=1}^{N} \chi_i + \delta = 1$, where $\chi_i \geq 0 \ \ \forall i$, and $\delta \geq 0$.[10]

6. *Interregional spillover*: $\sum_{s=1}^{S} \eta_s \sum_{j=1}^{N} w_{ij} \dot{TFP}_{jt-s}$. Interregional intra and intersectoral spillover is here modelled through lagged TFP and not directly through R&D, not only because, as mentioned, we have not data on regional-level agricultural R&D, but mostly because spillover can either come from other regions' R&D or from other sources, namely learning processes themselves (Bakus et al, 1992; Matsuyama, 1992; Caniëls, 2000; Keilbach, 2001). Therefore, interregional spillover is here modelled through the following term: $\sum_{s=1}^{S} \eta_s \sum_{j=1}^{N} w_{ij} \dot{TFP}_{jt-s}, \forall j = 1,...,N, \ \forall s = 1,...,S$ where w_{ij}'s are region-specific normalized weights expressing spatial contiguity,[11] and η_s 's express the spillover effect on TFP.

[10] Overall increasing returns to scale in (1) are eventually motivated by two effects: the direct contribution of R&D to production (β) and partial non-rivalry of public agricultural R&D (δ).

[11] w_{ij}'s are elements of a NxN matrix (**W**) where, for i-th region, w_{ii} =0 and w_{ij} =0 (if the j-th region is not contiguous) or w_{ij} =1/M (when j-th region is one of the M border regions). In fact, calculating technological spillovers just on the base of geographical contiguity among regions is definitely rough. It should proxy the real flow of technology and knowledge but this actually more influenced by the "economic distance" rather than the geographical distance (for a more sophisticated treatment of spatial models taking into account this kind of distance see also Conley, 1999). Nevertheless, this kind of solution often implies availability of much more detailed information on interregional flows, especially those that may somehow incorporate knowledge, such as traded goods, physical and human capital. This sort of information at regional level and over the whole period is largely lacking or incomplete. For instance, accurate database on Italian regional economies almost entirely disregard interregional flows (Paci and Saba, 1997). Nonetheless, it should be acknowledged that current available information at regional level and over time still allows to better detect which regions are closer in terms of, for instance, economic structure and specialization (i.e., sectoral composition), openness, innovative attitude, etc. (Abreu et al., 2004). On the base of these features, a more accurate definition of **W** and, consequently, of spillovers could be achieved. This can definitely be and interesting perspective for future empirical research on this subject.

Equation (2) is therefore rewritten as follows (see Table 2 for a detailed explanation of expected parameter values and signs):[12]

(3)

$$\dot{TFP}_{it} = \underbrace{\left(\lambda_i + \ln\tilde{\beta}_i\right) + \rho\,\dot{TFP}_{it-1} + \tilde{\varphi}\,\dot{Y}_{it} + \rlap{$\overbrace{\phantom{\beta\phi\,\dot{R}_{Eit} + \beta\sum_{i=1}^{N-1}\chi_i\,D_i\,\dot{R}_{At} + \beta\delta\,\dot{R}_{At} + \sum_{s=1}^{S}\eta_s\sum_{j=1}^{N}w_{ij}\,\dot{TFP}_{jt-s}}}^{\dot{R}_{it}}$}\beta\phi\,\dot{R}_{Eit} + \beta\sum_{i=1}^{N-1}\chi_i\,D_i\,\dot{R}_{At}}_{\textit{Divergence factors (internal effects)}} + \underbrace{\beta\delta\,\dot{R}_{At} + \sum_{s=1}^{S}\eta_s\sum_{j=1}^{N}w_{ij}\,\dot{TFP}_{jt-s}}_{\textit{Convergence factors (external effects)}} + \varepsilon_{it}$$

where D_i's are region-specific dummies. Appending the usual spherical disturbance ε_{it}, i.i.d. N~(0,σ^2), equation (3) becomes a conventional dynamic panel model with Fixed Effects (FE) that, in fact, represent the *Idiosyncratic permanent component* of i-th region TFP growth (Table 2).[13]

This model makes explicit why, here, the emphasis is on TFP growth difference across regions rather than on TFP convergence by itself (Ball et al., 2004). There are indeed two different stream of empirical literature alternatively focusing on TFP growth or TFP level comparisons (Harrigan, 1997; McCunn and Huffman, 2000) and confusion is often made between the two, as well (Madsen, 2007). Emphasizing the former has three major

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[12] See also Park (2004) for a similar specification.

[13] These FE are often aimed at capturing unobservable heterogeneity across regions. Such heterogeneity, particularly in recent growth empirics, is frequently explained in terms of different presence, in quantity or quality, of informal institutions, social networks, ecc. (Knack and Keefer, 1997; Durlauf, 2002), whereas more formal institutions should not, at least in principle, differ too much across regions within the same country. Upon collection of appropriate data, these institutional aspects, especially if time-variant, could be also explicitly included in growth regressions as further explanatory variables and are, in fact, often considered among the most important determinants of regional growth patterns in the Italian case (Helliwell and Putnam, 1995). In the case of agriculture, for instance, a major role can be attributed to the differentiated application of policies (above all, the Common Agricultural Policy), though long-term regional data for these are often problematic (Esposti, 2007). Here, however, these intercept terms, as well as all other model variables, are strictly derived from the underlying theoretical framework in (1)-(2), thus we prefer to not include regressors that are not justified by that derivation and, above all, whose parameters have not a clear theoretical interpretation and implication as detailed in Table 2. Moreover, as explained in the result section, time-invariant heterogeneity does seem neither statistical significant nor particularly important in explaining regional TFP growth, so this would suggest a minor role also for time-invariant institutional variables.

justifications. Firstly, comparing TFP levels entails calculation of multilateral TFP indices and this, though methodologically well established since Caves et al. (1982), may incur in some relevant practical and interpretation problems (Rizzi and Pierani, 2006; Ball and Norton, 2002; McCunn and Huffman, 2000; Ball et al., 2004).[14] Secondly, it seems reasonable to admit a structural and permanent difference among agricultural TFP levels because of regional heterogeneity in terms of natural resources, climate conditions, historical characters that no catching-up can actually reduce (McCunn and Huffman, 2000, p.373-375).

The third, and more important, justification is theoretical. In fact, neoclassical growth theory (and the consequent growth convergence hypothesis) attributes a key-role to TFP growth rate in explaining steady-state growth. Evidently, if long-run/stable TFP growth is the same across units, TFP levels may differ only for the different initial values that we can attribute to the above-mentioned inescapable heterogeneity, but also eventually prevent regional TFP levels from converging.

After all, even though lagging behind regions showed higher TFP growth rates over a certain period (catching-up), this could not be a permanent evidence. In the longer run, once achieved TFP level convergence, we should rather observe prevalence of very close TFP growth rates (henceforth, we refer to this tendency toward equal TFP growth rates as the *TFP growth convergence hypothesis*). In fact, even if there was not TFP level convergence, it is still TFP growth convergence that makes economic sense in the long run as it signals the access to the same technological advancements, that is regions move along the same technological trajectory. On the contrary, if TFP growth convergence was not observed, as divergence forces prevail, TFP level convergence would be just a temporary evidence, if any.

[14] In particular, there is no natural ordering in spatial (cross-sectional) data, comparable to chronological ordering for time series. Thus, multilateral productivity comparisons within panel data may provide different evidence according to which point in space (i.e., region) is selected as reference (Ball and Norton, 2002; Ball et al., 2004).

Therefore, over a long-enough time period, the key issue (in both theoretical and empirical terms) is how TFP growth is formed across regions and whether convergence forces prevail on divergence ones. These forces are all displayed in equation (3) that eventually combines factors concerning temporary catching-up (e.g., through spillovers) with longer-term processes. This long enough term is here the post-WWII period. Figure 1 shows that in Italy, over those years, there is no clear-cut evidence concerning how regional agricultural TFP growth behaves in this respect. Among highest TFP growth rates we find regions belonging to the richer part of the country, even in agricultural terms (i..e, Northern Italy). In particular, the highest average TFP growth rate is observed in Liguria (3,2% per year), which is a rich Northern Italian region with highly intensive agriculture; the lowest value concerns Sardegna (0,9% per year), a region belonging to the less developed part of the country (Centre-South) with a mostly extensive agriculture.

The main empirical question behind equation (3) thus becomes whether convergence forces prevail on divergence ones, eventually making regional TFP growth differences just temporary and, consequently, statistically not significant in the longer run. Hence, this hypothesis of TFP growth convergence can be simply tested by computing the difference between regional and aggregate (national) TFP growth rates and, then, testing for nonstationarity according to the following equation (Martin and Mitra, 2001; Enders, 1995, p.225):

$$(4)\quad \Delta D_{it} = \mu_i + \rho_i D_{it-1} + \sum_{s=1}^{S} \pi \Delta D_{it-s} + \beta t + e_{it}$$

where $D_{it} = \dot{TFP}_{it} - \dot{TFP}_t^N$, TFP_t^N is the aggregate (national) agricultural TFP growth rate and e_{it} is a spherical disturbance term. Equation (4) is a conventional Augmented Dickey-Fuller (ADF) unit-root test with intercept and deterministic trend. For TFP growth convergence to be observed, we must reject the hypothesis of unit root (namely, $\rho \neq 0$) and find not significant intercept and deterministic trend (namely, $\mu_i, \beta = 0$). In other words, D_{it} must behave as: $\Delta D_{it} = \rho_i D_{it-1} + e_{it}$ with $\rho \neq 0$.

4. Data

The model (equations (3) and (4)) is here applied to the 20 Italian (NUTSII) regions over the post-WWII period (1951-2002). The dataset, thus, includes 1040 observations of the four model variables, TFP_{it}, Y_{it}, R_{Eit}, R_{At}. The time trend *t* and 19 regional dummies[15] complete the information set. Y_{it} is the value of regional agricultural production expressed in 1995 prices (millions €). Regional series are taken from the 1951-2002 AGREFIT database (Rizzi and Pierani, 2006). TFP_{it} is taken from the same database and computed by Rizzi and Pierani (2006) aggregating outputs and inputs with chain Fisher ideal indexes. These are not multilateral TFP indices, thus do not allow direct comparison of TFP across regions, though still make TFP growth rates fully comparable. As interest here is on TFP growth differences and not on TFP level convergence, the calculation of an appropriate multilateral TPF index is not required.

R_{At} is the national public agricultural R&D stock expressed in 1995 millions €. Sources of public agricultural R&D data to 2002 are detailed in Esposti and Pierani (2000; 2006b). Respective investments in nominal terms are deflated using to the specific public agricultural R&D deflator calculated by Esposti and Pierani (2006b). R&D stock series are then computed from investment data using methodology and parameters discussed in Esposti and Pierani (2003). We apply this same methodology to reconstruct the R_{Eit} stock series from the respective non-agricultural investment (expressed in 1995 millions €) (Park, 2004). For R_{Eit},

[15] To avoid singularity, the dummy of Valle d'Aosta is dropped. As this is the smallest Italian region, such selection makes approximation $\beta \cong \beta\left(\delta + \sum_{i=1}^{N-1} \chi_i\right)$ more strictly hold (see Table 2).

harmonized regional data are taken from 1975 onwards from CRENoS (Paci and Saba, 1997) and ISTAT/EUROSTAT databases (Sterlacchini and Venturini, 2007). Over the 1965-1974 period only aggregate (national) data are available, while this information is missing from 1952 to 1964. Over years 1965-1974, regional data have been thus computed by distributing national values across regions according to the respective R&D gross investment rates observed from 1975 to 2002. Regional values from 1952 to 1965 have been finally reconstructed applying the backward procedure discussed in Esposti and Pierani (2003).

5. Econometric issues

Estimation of equation (3) entails three major econometric issues. The first concerns stationarity of model variables over T preventing spurious regression. The initial estimation step thus tests for the presence of unit roots in model variables. Among possible alternative unit-root tests proposed for panel data (Baltagi, 2005; Hsiao, 2003), the IPS test (Im et al., 2003) is here adopted. It has become widely used in the empirical literature as it outperforms the LLC (Levin, Lin and Chu) test and should be especially preferred when N is fixed and T tends to be greater (possibly, $T \rightarrow \infty$) (Baltagi, 2005, p. 247; Karlsson and Löthgren, 2000).

The second issue relates to the assumption of spherical disturbances that excludes Cross-sectional Dependence (CD) of the error term across the N units. In fact, a major drawback of IPS panel unit-root test concerns the underlying assumption of cross-sectional independence. This is evidently a strong assumption in the present case as linkages across regions are acknowledged through spillovers. Disregarding CD in designing unit-root tests may lead to wrongly reject nonstastionarity and, more generally, to undesirable finite sample properties of the IPS test itself (Pesaran, 2007; see also Mikhed and Zemĉik, 2007, for a clear overview). To deal with this latter issue, the so-called second-generation panel unit-root tests, admitting CD, can be alternatively adopted (Baltagi, 2005 p. 247-250; Pesaran, 2007). The general diagnostic test for cross-sectional dependence (CD test) proposed by Pesaran (2004) is therefore applied.[16] If such test rejects the hypothesis of cross-sectional independence, one viable solution is to perform individual Cross-sectionally Augmented Dickey-Fuller (CADF), then finally assessing nonstationarity within the panel with the Cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007).[17]

This same approach to panel unit-root testing is adopted to asses TFP growth convergence according to equation (4). In this case, abovementioned CIPS test assesses stationarity within the panel under CD, while individual unit-root ADF tests are performed to evaluate the presence of intercept and deterministic trend (Enders 1995, p. 257).

The third major econometric issue concerns the presence of the lagged dependent variable ($\dot{TFP}_{it-1}$) among regressors, that is the AR(1) terms of equation (3). This term makes conventional panel Least Squares (LS) estimators potentially incur into the so-called Nickell bias (Arellano, 2003, p. 85; Esposti, 2007). LSDV (Least Squares with Dummy Variables) estimates are consistent whenever T goes to infinity (Arellano, 2003, p. 90), but are biased in the small sample and this bias may be large. Even though in the present case (i.e., N=20 and T = 52) bias is expected to be small, beside OLS-pooled and LSDV, we also perform Arellano-

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[16] When T>N, as in the present case, the Breusch-Pagan LM test also performs well (Baltagi, 2005, p. 247). Nonetheless, we prefer the Pesaran (2004) test because it is relatively simple and naturally linked to the following CIPS test, and because it is becoming popular and widely used for its validity regardless the relative and absolute size of T and N (Pesaran, 2007).

[17] In principle, if present, cross-sectional dependence can also undermine estimation of equation (3) itself. Conventional panel estimators, especially when spatial panels (i.e, with countries or regions as observation units) are used and linkages among units are explicit (spillovers across regions or countries is a typical case; Baltagi, 2007 p. 197), may be inefficient or even biased estimates in either Fixed-Effects (FE) or Random-Effects (RE) specifications (De Hoyos and Sarafidis, 2006). These problems are amplified in dynamic models and when T is fixed and N tends to be greater (possibly, $N\rightarrow\infty$), which is not, however, the present case (De Hoyos and Sarafidis, 2006). It must be noticed, however, that viable solutions to estimation under CD may also entail the introduction of spatial linkages expressing correlations across contiguous units (Hsiao, 2003, p. 309-310, Baltagi, 2005, p. 197-200) also in the form of spatially lagged dependent or independent variables (Haining, 1990; LeSage, 1999). Therefore, in equation (3) this correction is already achieved through the inclusion of spatially lagged TFP values taking into account spillovers from contiguous regions (see also Abreu et al., 2004, for a similar application).

Bond GMM estimation.[18] Such estimation should prevent this bias, in principle, but its small-sample performance is unpredictable and practical aspects (namely, the choice of instruments) may be particularly critical in this respect (Hsiao, 2003; Arellano, 2003, p. 120).

6. Results

6.1. TFP growth convergence and unit-root tests

Table 3 reports unit-root tests on D_{it} (equation (4)), therefore on TFP growth convergence hypothesis. Within the panel, and regardless the specification (with or without intercept and trend), the presence of CD is largely accepted. Results of the IPS test, therefore, must be confirmed by correcting for CD, i.e. by the CIPS test. Evidently, IPS and CIPS are concordant in rejecting unit-root in D_{it} . To fully assess TFP growth convergence, however, it must be noticed that individual unit-root tests confirm rejection of unit-root in D_{it} in all regions. Moreover, intercept and deterministic trend are not statistically significant, the only exceptions being Lombardia, Piemonte and Trentino Alto-Adige, three contiguous Northern regions, whose statistically significant negative intercept suggests a constantly lower TFP growth rate with respect to the national average. In all other cases, the hypothesis of TFP growth convergence is fully supported by data.

Table 4 displays panel unit-root tests on equation (3) variables.[19] Evidence is clear, regardless the adopted test specification. All model variables are stationary though, at the

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[18] We only use the One-step GMM estimator (Arellano, 2003). In fact, though asymptotically efficient, the two-step GMM estimator actually shows significantly downward biased standard errors in small samples. Therefore, particularly for statistical inference, an appropriate correction should be made accordingly (Windmeijer, 2005). Moreover, here we always refer to the so-called GMM-DIFF estimator, while the GMM-SYS estimate is not considered (see Arellano, 2003, for more details on this aspect, and Esposti, 2007, for a recent application of both estimators). As results suggest low persistence of TFP growth (i.e., $\rho << 1$), under this circumstance the improvement provided by GMM-SYS estimation is expected to be negligible (Arellano, 2003).

[19] Due to space limit, and given the clear results emerging from panel unit-root tests, individual ADF tests are not reported. These are consistent with panel tests and are available upon request.

same time, all tests suggest cross-sectional dependence. With respect to the adopted empirical model, we can conclude that equation (3) do not incur in spurious regression problems and hence represents an appropriate specification and also the inclusion of spatially-lagged dependent variables, taking into account the observed spatial dependence, seems appropriate.

6.2. Model estimates

Equation (3) estimates are shown in Table 5. Firstly, OLS-pooled results (where constant term is assumed equal across regions) can be compared with the LSDV estimates (i.e., where FE are admitted). For most parameters, estimates are very close in the two cases (and R^2, as well), major differences emerging only for few χ_i's and, consequently, for indirect parameters β. This is confirmed by the F-test on region-specific fixed-effects indicating that these terms are not statistically different across regions.[20] As TFP growth convergence is accepted, it should not surprise that exogenous technical change rate and learning on "old processes" are the same across regions (see Table 2).

Although OLS-pooled and LSDV estimators can be thus considered as statistically equivalent, it should be reminded that both may produce biased estimate for the presence of the AR term, whereas GMM estimates are, in fact, consistent. Tests on GMM estimation confirm that both selection of instruments (Sargan test) and AR(1) specification (LM tests) are appropriate. GMM results present some differences with respect to LS previous estimates,

[20] These fixed effects actually represent the term $\left(\lambda_i + \ln \tilde{\beta}_i\right)$ in (3) as also detailed in Table 2. Therefore, it may be of interest to investigate further what lies behind this observed regional heterogeneity. According to the estimator adopted, in fact, these FE can be obtained either directly (through dummies) or indirectly (in first-difference specifications, as in the case of GMM estimation). Once estimated, these FE could be thus regressed with possible explanatory variables such as institutional variables or geographical dummies that are at once time-invariant and significantly heterogeneous across regions. As mentioned, linking TFP growth performance to institutional variables is very frequent in recent empirical literature. Nonetheless, this second investigation step would just entail a cross-sectional regression with very few observations (i.e., 20) and we may not expect very significant or consistent results. Moreover, estimation results themselves show that, on average, this idiosyncratic component is almost irrelevant in explaining TFP divergence/convergence, while F-test indicates that FE are not statistically different across regions. For these reasons, such further investigation is here skipped. Nonetheless, it can be an interesting idea to be developed in further studies, possibly with more observations under consideration (Italian provinces or EU regions, for instance).

but they do not substantially alter the overall picture. The most evident discrepancy concerns statistically significance of parameters. Under GMM, just two χ_i's are different from 0, while for other model parameters statistical significance mostly improves. The constant term, however, is now not statistically significant.

Therefore, regardless the adopted estimator, the economic interpretation of results is largely correspondent. Firstly, the constant term assumes a fairly small value. It should indicate exogenous technical change rate and learning on “old processes” in the dropped region (Valle d’Aosta) but, as discussed, it is not very much different from other regions’ fixed-effects. We can thus conclude that both exogenous technical change and learning-on-“old processes” rates are <.010, lower than values reported in previous studies (Table 2).

Secondly, the autoregressive component, albeit statistically significant, indicates limited persistence (about -.15), which is consistent with unit-root tests and justify the adoption of the GMM-DIFF, estimator instead of GMM-SYS estimator. Thirdly, parameter associated to the learning component is statistically significant and very close in the three alternative estimates, i.e. about .55-.60. This value is much larger that what reported by Gopinah and Roe (1997) for U.S. agriculture.

Less clear-cut results emerge for R&D and spillover variables. Interregional spillover, proxied by spatially lagged TFP is significant for both lags only in GMM estimation.[21] Nonetheless, values are quite close in three estimations and the overall spillover effect (i.e., the sum of η_1 and η_2) is about .375. It is a remarkably high value if compared to some previous estimates of interregional (or international) spillover (Park, 2004), but consistent with results reported by Esposti (2000b) for Italian agriculture (Table 2).

[21] Following equation (3), s=2 is assumed, i.e one-year (η_1) and two-year (η_2) lags of spatially lagged TFP are included as regressors.

On the contrary, intraregional intersectoral spillover is small and not statically significant; even for this parameter, the three estimators provide similar results with $\beta\phi$ ranging between .010 and .017. However, if we consider the implicit value of ϕ as derived by indirect estimation of β, value obtained with LSDV is much higher (about .080), though still lower than results previously reported for intersectoral spillover in agriculture (Table 2).

Finally, parameters associated to public agricultural R&D incorporate three different effects. Firstly, β indicates returns to R&D stock (β being its parameter in the Cobb-Douglas production function). The three estimates of β range between .65 and .20, but it is statistically significant only under OLS-pooled estimation. Nonetheless, such returns are remarkably high when compared to previous estimate (Table 2). Secondly, the distinction between a common and region-specific part indicates that the former (expressed by δ, implicitly derived from β estimates) is either not statistically different from 0 or implausibly negative in the case of OLS-pooled estimate. Region-specific parts (χ_i's) are statistically significant in few cases (2 regions in the GMM estimation, 8 in LSDV), but their size would suggest a larger value that the common component (δ).

6.3. Decomposition of TFP growth

The relative importance of different drivers of TFP growth, however, can not be simply evaluated by looking at the estimated parameters. Beside them, directly interpretable as elasticities, the overall variation of the respective variables is also relevant. Table 6 decomposes the overall TFP growth rate (averaged over the whole panel)[22] into the seven components indicated in Table 2. Percentage contributions to TFP growth have been computed by simply taking the estimated (GMM) parameters and the average growth rates (over the whole panel) of respective model variables.

[22] Region-by-region decomposition is available upon request.

It emerges that major driving forces of TFP growth are interregional spillover, learning and public agricultural R&D. This latter, however, mostly impact productivity through its region-specific part (χ_i's), as the common component (δ) shows a very limited contribution. Idiosyncratic component and intraregional spillover are almost negligible, too, while the autoregressive term corrects TFP growth rates downward for about 18% per year.

By assigning these effects to the two groups of "convergence" and "divergence" forces, we obtain an almost perfect equilibrium: forces favouring TFP growth convergence (mostly, interregional spillover) are almost completely counterbalanced by forces acting individually across regions (learning and region-specific public R&D). It is also worth stressing that public agricultural R&D, whose alleged effect should go in the direction of common TFP growth trajectories, actually behaves as a divergence force. Convergence factors slightly prevail, eventually, and this confirm results obtained in terms of TFP growth convergence, but this prevalence does not seem strong enough to justify that clear-cut evidence. In this respect, therefore, further investigations might clarify the point.

7. Concluding remarks

Empirical literature has often investigated the hypothesis of TFP level convergence, even with specific emphasis on agriculture. Less frequently, however, attention concerned whether long-run TFP growth rates actually tend to be equal across units (sectors, countries or regions). The primal purpose of this paper is to test such hypothesis of TFP growth convergence, and to analyse its major drivers. In particular, forces tending to level TFP growth rates and others instead generating individual TFP patterns are identified and their magnitude compared.

The empirical application concerns agricultural production in Italian regions during the post-WWII period, thus the panel covers quite a long time period as well as significantly heterogeneous agricultural characters, though still within a common national context, hence same regulations, policies and overall development trajectory. Empirical evidence supports TFP growth convergence, that is, TFP growth is quite close across regions, but also suggests that convergence and divergence forces almost perfectly offset.

Among these forces, of particular interest is the role of public R&D in prevalently generating region-specific effects, together with learning, but also the major contribution of interregional spillover to eventually induce convergence. On these key-forces, on how they are computed, how they operate and reciprocally combine, however, future research should concentrate further attention.

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Table 1 – Drivers of regional agricultural TFP growth

Driving Forces	***Intended/Unintended Effects***	***General case (farm/firm, sector, region, country)***	***Specific case: regional agricultural TFP***
Internal effects Divergence forces	Intended effects	- Own (private) R&D	Intraregional effects: - Region-specific part of public R&D
	Unintended effects	- Idiosyncratic permanent and cyclical TFP growth - Scale or cumulative effects (i.e., learning, dynamic economies of scale, Verdoorn-Kaldor law, etc.)	Intraregional effects: - Idiosyncratic permanent and cyclical TFP growth - Intraregional intersectoral spillovers - Scale or cumulative effects
External effects Convergence forces	Intended effects	- Public R&D	Interregional effects: - Common part of public R&D
	Unintended effects	- (International, Intersectoral, Interregional) Spillovers	Interregional effects: - Interregional (intra and intersectoral) spillovers

Table 2 - Expected sign and theoretical values of model parameters (equation (3))

Forces	***Effects***	***Theoretical parameter values***
Divergence forces	1.*Autoregressive component*	-1< ρ <1, for stationary series, and close to 0 in case of low persistence.
	2.*Idiosyncratic permanent component*	$\left(\lambda_i + \ln\tilde{\beta}_i\right)$>0, as both λ_i and $\ln\tilde{\beta}_i$ are expected to be ≥0. For Italian agriculture, Esposti and Pierani (2000) report an estimate of λ ranging between .02-.03. $\ln\tilde{\beta}_i$ expresses the learning effect that remains even when output is constant (thus, distinguishing learning on "old processes" from learning on "new processes", i.e. φ). Govindan et al. (1996) report a non-statistically significant estimate of $\ln\tilde{\beta}_i$.
	3.*Learning*	$0<\varphi<1$, for diminishing returns in learning. This parameter is also called *speed of learning* (Randon and Naimzada, 2006, p.99) however with a different interpretation with respect to the present specification. With an analogous approach to U.S. agriculture¸ Gopinath and Roe (1997, Table 4B) find a non-statistically significant value, always lower than .0001.
	4.*Intraregional intersectoral spillover*	$0<\phi<1$, hence $0<\beta\phi<\beta$, as confirmed by Park (2004, Tables 4-6) where, for non-manufacturing, values of ϕ ranging between .047 and .057 are reported. For Italian agriculture, Esposti (2000b) reports an estimate of .028. As we actually estimate $\beta\phi$, ϕ can be indirectly computed once estimated β (see 5a).
	5a.*Public agricultural R&D: region-specific part*	$0<\beta,\delta,\chi_i<1, \forall i$, thus $0<\beta\delta,\beta\chi_i<1, \forall i$ with $\delta+\sum_{i=1}^{N}\chi_i = 1$. As we only estimate (N-1) χ_i parameters, we can indirectly compute β from $\beta \cong \beta\left(\delta+\sum_{i=1}^{N-1}\chi_i\right)$ provided that the dropped region is a small one ($\chi_N \cong 0$). Esposti and Pierani (2003) find a value of β ranging between .05 and .20 for Italian agriculture. Park (2004, Tables 4-6) reports β around .10 for non-manufacturing.
Convergence forces	5b.*Public agricultural R&D: common part*	See 5a.
	6.*Interregional spillover*	$0<\eta_s<1, \forall s$ (Randon and Naimzada, 2006, p.99). Park (2004, Tables 4-6) confirms this result for R&D international spillover in non-manufacturing. For Italian agriculture, Esposti (2000b) reports for $\sum_s \eta_s$ an estimate of .594.

Table 3 – Panel and individual unit-root tests on D_{it} (equation (4)) – standard error in parenthesis

Panel unit-root tests	With intercept and trend	With intercept, no trend	No intercept, no trend
IPS	-16.134*	-17.395*	-16.718*
CD	-2.196*	-2.182*	-2.295*
CIPS	-6.698*	-6.583*	-6.448*
Individual unit-root tests (ADF)		***Parameters***	
	ρ	μ	β
Northern regions			
Friuli	-2.126* (.370)	-.0188 (.015)	.001 (.001)
Liguria	-1.407* (.322)	.004 (.032)	.0005 (.0010)
Lombardia	-2.120* (.292)	-.018* (.008)	.0005 (.0003)
Piemonte	-1.924* (.355)	-.026* (.012)	.0004 (.0003)
Trentino Alto-Adige	-2.514* (.404)	-.035* (.016)	.0008 (.0005)
Veneto	-1.849* (.360)	.005 (.011)	.0001 (.0003)
Valle d'Aosta	-1.654* (.307)	-.013 (.015)	.0001 (.0004)
Central regions			
Abruzzo	-2.700* (.361)	.023 (.013)	-.001 (.001)
Emilia-Romagna	-1.891* (.336)	-.004 (.012)	-.000 (.001)
Lazio	-2.086* (.350)	.016 (.011)	-.0004 (.0003)
Marche	-1.480* (.331)	-.005 (.013)	.0002 (.0004)
Toscana	-2.367* (.363)	.007 (.014)	.0000 (.0004)
Umbria	-1.982* (.355)	-.015 (.011)	.0008 (.0004)
Southern regions			
Basilicata	-2.401* (.331)	.009 (.031)	-.001 (.001)
Campania	-.884* (.177)	.008 (.012)	.000 (.001)
Calabria	-2.074* (.379)	.030 (.027)	-.001 (.001)
Molise	-2.104* (.331)	-.001 (.023)	.0001 (.0007)
Puglia	-2.989* (.403)	.013 (.027)	-.0004 (.0008)
Sardegna	-1.445* (.367)	-.021 (.018)	.0002 (.0006)
Sicilia	-1.986* (.343)	-.022 (.019)	-.0008 (.0006)

*denotes statistical significance at 5% confidence level

Note: For CIPS tests critical values are taken from Pesaran (2007); all tests admit one-year lag (s=1)

Table 4 – Panel unit-root tests on model variables (equation (3))

Model Variables **Panel unit-root tests**	With intercept and trend	With intercept, no trend	No intercept, no trend
$\dot{TFP}$			
IPS	-13.061*	-15.037*	-7.687*
CD	16.172*	15.912*	14.013*
CIPS	-5.057*	-5.012*	-5.168*
$\dot{Y}_{it}$			
IPS	-14.036*	-14.421*	-12.127*
CD	20.586*	22.929*	20.192*
CIPS	-5.497*	-5.506*	-5.283*
$\dot{R}_{Eit}$			
IPS	-13.361*	-12.031*	-5.216*
CD	50.629*	48.809*	50.007*
CIPS	-4.012*	-3.787*	-3.347*
$\dot{R}_{At}$ [23]			
ADF	-6.423*	-4.844*	-2.892*

*denotes statistical significance at 5% confidence level

Note: For CIPS tests critical values are taken from Pesaran (2007); all tests admit one-year lag (s=1)

[23] In fact, R_{At} has only a time-series dimension, as we do not observe regional data for it. Non-stationarity is thus tested through a conventional ADF test.

Table 5 – OLS-pooled, LSDV and GMM estimates of equation (3) - standard error in parenthesis

Parameter	OLS-Pooled	LSDV	GMM
$\left(\lambda_i + \ln \tilde{\beta}_i\right)$	.011*	.008*	.001
	(.002)	(.003)	(.001)
ρ	-.142*	-.148*	-.161*
	(.070)	(.073)	(.024)
$\tilde{\varphi}$	.599*	.596*	.550*
	(.160)	(.161)	(.019)
η_1	.226	.229	.236*
	(.118)	(.119)	(.033)
η_2	.126*	.131*	.140*
	(.062)	(.063)	(.034)
$\beta\phi$	.012	.017	.011
	(.029)	(.030)	(.032)
$\beta\delta$	-.076*	-.053	.017
	(.021)	(.043)	(.130)
$\beta\chi_{AB}$	.102*	.075*	.107
	(.006)	(.016)	(.094)
$\beta\chi_{BA}$	.010	-.126	-.078
	(.022)	(.072)	(.081)
$\beta\chi_{CA}$	.106*	.063*	.118
	(.008)	(.014)	(.092)
$\beta\chi_{CL}$	.042	.054*	.069
	(.024)	(.009)	(.090)
$\beta\chi_{ER}$	.050*	.099*	.105
	(.010)	(.035)	(.092)
$\beta\chi_{FR}$	.016	-.042	-.039
	(.009)	(.060)	(.086)
$\beta\chi_{LA}$	.046*	.016	-.005
	(.008)	(.029)	(.089)
$\beta\chi_{LI}$	.129*	-.067	-.099
	(.004)	(.040)	(.081)
$\beta\chi_{LO}$	.011*	.032	.033
	(.003)	(.035)	(.099)
$\beta\chi_{MA}$	.072*	.048	.113
	(.011)	(.031)	(.084)
$\beta\chi_{MO}$	-.013	-.104*	-.182*
	(.017)	(.039)	(.085)
$\beta\chi_{PI}$	-.005	.036	.099
	(.013)	(.023)	(.085)
$\beta\chi_{PU}$	.040*	.115*	.192*
	(.015)	(.014)	(.083)
$\beta\chi_{SA}$	-.119*	-.093	-.089
	(.020)	(.068)	(.087)
$\beta\chi_{SI}$	.072*	.066*	.125
	(.003)	(.019)	(.089)
$\beta\chi_{TO}$	.109*	.050	.090
	(.015)	(.030)	(.086)
$\beta\chi_{TR}$	-.068*	-.003	-.029
	(.004)	(.055)	(.094)
$\beta\chi_{UM}$	.056*	-.031	-.005
	(.004)	(.027)	(.081)
$\beta\chi_{VE}$	.077*	.082*	.100
	(.009)	(.026)	(.091)
Indirect parameter: β	.657*	.216	.641
	(.081)	(.622)	(.430)
H0: $\left(\lambda_i + \ln \tilde{\beta}_i\right) = \left(\lambda_j + \ln \tilde{\beta}_j\right), \forall i, j$ (F-test)	-	.789	
Adj. R^2	.724	.723	
LM-1 test			-3.591*
LM-2 test			-1.319
Sargan test			3.302

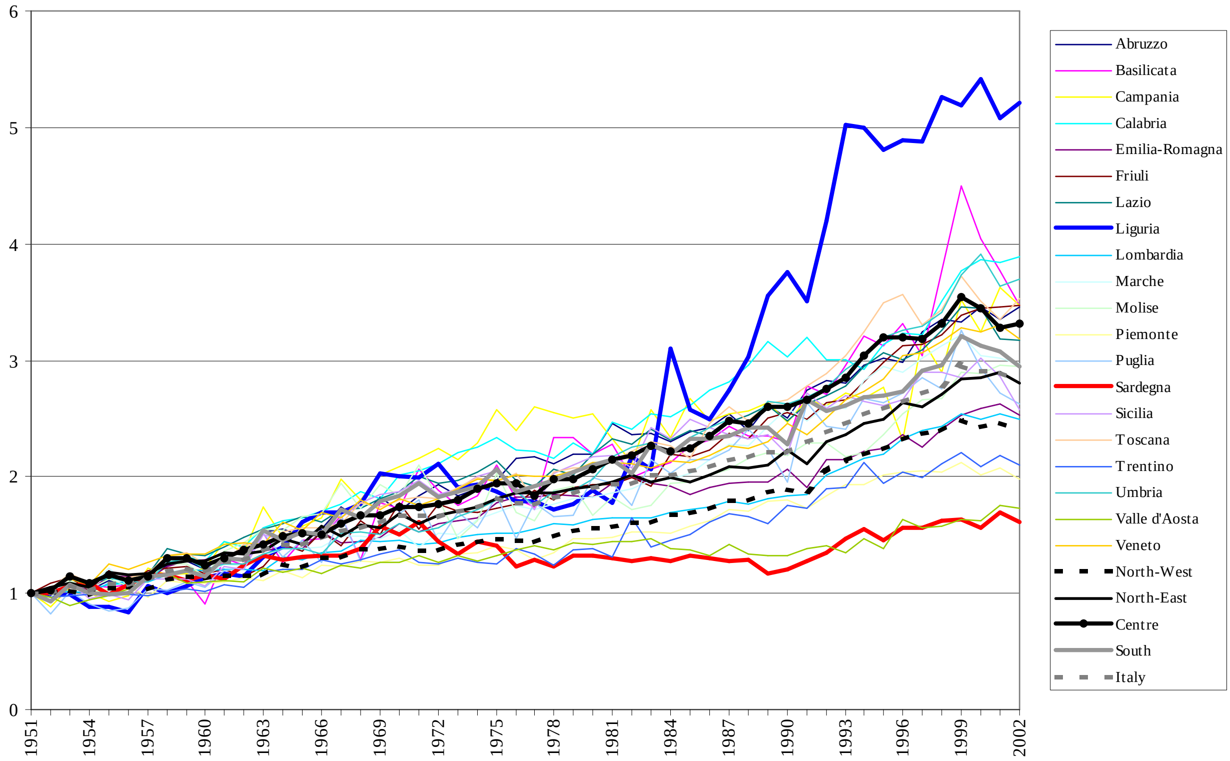
*denotes statistical significance at 5% confidence level

Note: AB=Abruzzo, BA=Basilicata, CA=Campania, CL=Calabria, ER=Emilia-Romagna, FR=Friuli Venezia Giulia, LA=Lazio, LI=Liguria, LO=Lombardia, MA=Marche, MO=Molise, PI=Piemonte, PU=Puglia, SA=Sardegna, SI=Sicilia, TO=Toscana, TR=Trentino Alto Adige, UM=Umbria, VA=Valle d'Aosta, VE=Veneto

Table 6 – Aggregate TFP growth decomposition – sample averages, GMM estimates

Effects	***% Contribution***
1. Autoregressive component	-18,51%
2. Idiosyncratic permanent component	5,53%
3. Learning	38,01%
4. Intraregional intersectoral spillover	1,82%
5a. Public agricultural R&D: region-specific part	22,04%
Divergence forces	**48,89%**
5b. Public agricultural R&D: common part	6,43%
6. Interregional spillover	44,68%
Convergence forces	**51,11%**
Total TFP Growth rate	**100,00%**

Figure 1 – Individual regional agricultural TFP - macro-regions and extreme cases in bold



Source: Adaptation from Rizzi and Pierani (2006)