Why Should Regional Agricultural Productivity Growth Converge? Evidence from Italian Regions

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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. 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, Panel Data**

I. DRIVING FORCES OF TFP GROWTH: A SHORT OVERVIEW

Several empirical contributions investigated agricultural productivity differences across countries and states and also attempted to explain why these differences may permanently occur, [1], [2], [3], [4], [5], [6]. Following this stream of research, this paper analyses agricultural Total Factor Productivity (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 also paying attention to its major drivers, [7], [8], [9], [10]. More recently, emphasis have been put also on regional differences in this respect, [9], [11], [12], [13], [14].

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*, often interpreted as unintended consequences), [15].

For a given unit of observation (a farm/firm, a country, a region), internal effects firstly concern own R&D effort, but also often unintended cumulative processes usually as consequence of learning. In addition, individual productivity patterns may be driven by idiosyncratic, permanent as well as short-term or cyclical, characters. All these 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*). Two other forces, however, operate outside the limits of a any specific unit: public R&D investments and spillover effects. 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).

Agriculture, in particular, presents some specific characters in this respect. 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 [16]. 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. Moreover, 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 regional agricultures.

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, [6], and spillovers, [2], [17], affect agricultural TFP, not much has been done in understanding whether these effects actually facilitate TFP growth levelling across units of observation.

II. THE MODEL

We consider, as units of observation, *N* regional agricultural sectors observed over *T* years. Following a widely used representation [23], 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:

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

where Y_{it} is agricultural output, L_{it} and K_{it} are the conventional agricultural labour and capital inputs, respectively;[1] for these conventional factors of production, constant returns to scale are assumed. Non conventional production factors are in square brackets: R_{it} indicates 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),[2] we obtain the conventional non-parametric measure of TFP growth, or Solow residual[3]:

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

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 1):

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, [24].
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 (*Verdoorn-Kaldor Law*). Productivity growth generated by increasing scale of production is often associated to learning processes (thus, here identified as “learning component”, for simplicity). In fact, learning[4] has been often modelled as a scale effect with major long-term growth implications. [23] model this effect as $S_{it} = S_{it-1}(1+\beta_i Y_{it})^{\varphi_i}$, thus $\dot{S}_{it} \cong \ln \beta_i + \varphi_i \ln Y_{it}$ whenever $(1+\beta_i Y_{it}) \cong (\beta_i Y_{it})$, but it may also assume more complex functional forms, [19]. In the case of geographical units (countries or regions), however, it seems more realistic and suitable to return to the original Verdoorn-Kaldor formulation, that is, to assume *TFP level be an increasing function of cumulative output*, [15], [23, p.382], namely, 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. [20] use this

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[1] K aggregates also agricultural land and materials, [12].

[2] For a generic variable x_{it}, $\dot{x}_{it} = \dfrac{\partial \ln x_{it}}{\partial t}$.

[3] This conventional index-number TFP calculation implies constant returns to scale with respect to conventional inputs, and also assumes Hicks-neutral technical change and perfect competitive markets for output and conventional inputs, [12].

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

latter specification in estimating the causes of U.S. agricultural TFP growth.[5]

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.

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} .[6] 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 (national) expenditure; the second (5b) is the common (nation-wide) and non-rival part and equally applies to all regions. We can thus write: $\dot{R}_{At} = \sum_{i=1}^{N} \chi_i \dot{R}_{At} + \delta \dot{R}_{At}$, $\forall i = 1,\ldots,N$, 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 $\delta \geq 0$.[7]

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, [23], [15]. Therefore, interregional spillover is here modelled through the following term: $\sum_{s=1}^{S} \eta_s \sum_{j=1}^{N} w_{ij} \dot{TFP}_{jt-s}, \forall j = 1,\ldots,N, \ \forall s = 1,\ldots,S$ where w_{ij}'s are region-specific normalized weights expressing spatial contiguity,[8] and η_s 's express the spillover effect on TFP.

Equation (2) is therefore rewritten as follows (see Table 1 for a detailed explanation of expected parameter values and signs):

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[5] It should be noticed that learning is sometimes also modelled relating TFP growth (or cost reduction) to cumulative investments; the use of cumulative output, however, has become prevalent, [19].

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

[7] 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).

[8] 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).

$$\dot{TFP}_{it} = \underbrace{\left(\lambda_i + \ln\tilde{\beta}_i\right) + \rho\,\dot{TFP}_{it-1} + \tilde{\varphi}\,\dot{Y}_{it} + \mathrlap{\overbrace{\phantom{\beta\phi\,\dot{R}_{Eit} + \beta\sum_{i=1}^{N-1}\chi_i\,D_i\,\dot{R}_{At} + \beta\delta\,\dot{R}_{At}}}^{\dot{R}_{it}}}\beta\phi\,\dot{R}_{Eit} + \beta\sum_{i=1}^{N-1}\chi_i\,D_i\,\dot{R}_{At}}_{\textit{Divergence factors (internal effects)}} + \underbrace{\beta\delta\,\dot{R}_{At} + \sum_{s=1}^{S}\eta_s\sum_{j=1}^{N}w_{ij}\,\dot{TFP}_{jt-s}}_{\textit{Convergence factors (external effects)}} + \varepsilon_{it} \qquad (3)$$

where D_i’s are region-specific dummies.[9] 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). This model makes explicit why, here, the emphasis is on TFP growth difference across regions rather than on TFP convergence by itself, [3], [25]. Emphasizing the former has two major justifications. Firstly, 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 [3, p. 373-375].

The second, and more important, justification is theoretical. 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, in the longer run, whenever TFP level convergence was achieved, 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*). On the contrary, if TFP growth convergence was not observed, as divergence forces prevail, TFP level convergence would be just temporary evidence, if any. Therefore, over a long-enough time period, the key issue (in both theoretical and empirical terms) behind equation (3) 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, [5], [26, p.225]:

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

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 $\rho \neq 0$.

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

Table 1 Drivers of regional agricultural TFP growth and expected sign and theoretical values of model parameters (equation (3))

Forces	***Effects***	***Theoretical parameter values***
Internal effects ↓ 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, [7] 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). [18] 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* [19, p.99] however with a different interpretation with respect to the present specification. With an analogous approach to U.S. agriculture, [20, 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 [21, Tables 4-6] where, for non-manufacturing, values of ϕ ranging between .047 and .057 are reported. For Italian agriculture, [22] 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 ($\chi_N \cong 0$). [8] find a value of β ranging between .05 and .20 for Italian agriculture. [21, Tables 4-6] reports β around .10 for non-manufacturing.
External effects ↓ Convergence forces	5b.*Public agricultural R&D: common part*	See 5a.
	6.*Interregional spillover*	$0 < \eta_s < 1, \forall s$ [19, p.99]. [21, Tables 4-6] confirms this result for R&D international spillover in non-manufacturing. For Italian agriculture, [22] reports for $\sum_s \eta_s$ an estimate of .594.

III. 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}. Y_{it} is the value of regional agricultural production expressed in 1995 prices (millions €). Regional series are taken from the 1951-2002 AGREFIT database, [12]. TFP_{it} is taken from the same database and computed by [12] aggregating outputs and inputs with chain Fisher ideal indexes.[10]

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[10] These are not multilateral TFP indices, [25], thus do not allow direct comparison of TFP across regions, though still make TFP growth rates comparable. As interest here is on TFP growth differences, not on TFP level convergence, calculating 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 [7]. R&D stock series are computed from investment data using methodology and parameters discussed in [8]. We apply this same methodology to reconstruct the R_{Eit} stock series from the respective non-agricultural investment (expressed in 1995 millions €), [21]. For R_{Eit}, harmonized regional data are taken from CRENoS, [27], and ISTAT/EUROSTAT databases.

IV. 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, [28], the IPS test is here adopted.

The second issue relates to the assumption of spherical disturbances that excludes Cross-sectional Dependence (CD) of the error term across the N units. 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, [29]. The general diagnostic test for cross-sectional dependence (CD test) proposed by [30] is therefore applied. 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).[11] 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, [26, 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, [32, p. 85]. LSDV (Least Squares with Dummy Variables) estimates are consistent whenever T goes to infinity, [32, 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-Bond GMM estimation.[12]

V. RESULTS

A. TFP growth convergence and unit root tests

Table 2 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: except three regions, in all other cases the hypothesis of TFP growth convergence is fully supported by data.

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

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[11] In principle, if present, cross-sectional dependence can also undermine estimation of equation (3) itself. In (3), however, correction for CD is achieved through the inclusion of spatially lagged TFP values (see also [31] for a similar application).

[12] We only use the One-step GMM-DIFF estimator (see [32] for more details on this aspect).

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.

Table 2 – 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		Parameters ρ	 μ	 β
Northern regions							
Friuli (FR)	-2.126* (.370)	-.0188 (.015)	.001 (.001)	Marche (MA)	-1.480* (.331)	-.005 (.013)	.0002 (.0004)
Liguria (LI)	-1.407* (.322)	.004 (.032)	.0005 (.0010)	Toscana (TO)	-2.367* (.363)	.007 (.014)	.0000 (.0004)
Lombardia (LO)	-2.120* (.292)	-.018* (.008)	.0005 (.0003)	Umbria (UM)	-1.982* (.355)	-.015 (.011)	.0008 (.0004)
Piemonte (PI)	-1.924* (.355)	-.026* (.012)	.0004 (.0003)	*Southern regions*			
Trentino Alto-Adige (TR)	-2.514* (.404)	-.035* (.016)	.0008 (.0005)	Basilicata (BA)	-2.401* (.331)	.009 (.031)	-.001 (.001)
Veneto (VE)	-1.849* (.360)	.005 (.011)	.0001 (.0003)	Campania (CA)	-.884* (.177)	.008 (.012)	.000 (.001)
Valle d'Aosta	-1.654* (.307)	-.013 (.015)	.0001 (.0004)	Calabria (CL)	-2.074* (.379)	.030 (.027)	-.001 (.001)
Central regions				Molise (MO)	-2.104* (.331)	-.001 (.023)	.0001 (.0007)
Abruzzo (AB)	-2.700* (.361)	.023 (.013)	-.001 (.001)	Puglia (PU)	-2.989* (.403)	.013 (.027)	-.0004 (.0008)
Emilia-Romagna (ER)	-1.891* (.336)	-.004 (.012)	-.000 (.001)	Sardegna (SA)	-1.445* (.367)	-.021 (.018)	.0002 (.0006)
Lazio (LA)	-2.086* (.350)	.016 (.011)	-.0004 (.0003)	Sicilia (SI)	-1.986* (.343)	-.022 (.019)	-.0008 (.0006)

*denotes statistical significance at 5% confidence level. Note: For CIPS tests critical values are taken from [29]; all tests admit one-year lag (s=1)

Table 3 – 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*
$\dot{R}_{At}$ **			
ADF	-6.423*	-4.844*	-2.892*

*denotes statistical significance at 5% confidence level; ** 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. Note: For CIPS tests critical values are taken from [29]; all tests admit one-year lag (s=1)

B. Model estimates

Equation (3) estimates are shown in Table 4. 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. 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 1).

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, but they do not substantially alter the overall picture.

Table 4 – OLS-pooled, LSDV and GMM estimates of equation (3) - standard error in parenthesis

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

	OLS-Pooled	**LSDV**	**GMM**
H_0: $\left(\lambda_i + \ln\tilde{\beta}_i\right) = \left(\lambda_j + \ln\tilde{\beta}_j\right), \forall i, j$ (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

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 1). Secondly, the autoregressive component, albeit statistically significant, indicates limited persistence (about -.15) and, thirdly, parameter associated to the learning component is statistically significant and very close in the three alternative estimates, i.e. about .55-.60.

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.[13] 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 [22] for Italian agriculture (Table 1).

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 1).

Finally, parameters associated to public agricultural R&D incorporate three different effects. On the one hand, the three estimates of β, indicating returns to R&D stock, 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 1). On the other hand, 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).

C. 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 5 decomposes the overall TFP growth rate (averaged over the whole panel) into the seven components indicated in Table 1. 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.

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, further investigations are thus required.

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[13] 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.

Table 5 – 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%**

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