Agricultural Productivity in Space

An econometric assessment based on farm-level data

Edoardo Baldoni* and Roberto Esposti

Abstract

This work aims to investigate scale, scope and nature of spatial dependence of agricultural Total Factor Productivity (TFP) by using farm-level survey data. TFP is measured using transitive index numbers and the spatial properties of TFP are assessed within a dynamic spatial panel data model designed to separate production fundamentals from productivity spillovers. Because of the statistical issues that typically affect spatial analyses based on survey data, a Bayesian model selection procedure is used to inspect the spatial properties of TFP at different aggregation levels and to search for the most appropriate spatial scale to conduct the investigation. The application concerns Italian FADN farm-level data over the period 2008-2015 then aggregated at the NUTS3 level. Results suggest that agricultural productivity spillovers significantly occur though over a limited spatial range. The cumulated effects of the estimated diffusion mechanism are described through a set of spatial indicators and presented graphically.

Keywords: Dynamic Panel Models, Multilateral TFP index, Farm-level Survey Data, Productivity Spatial Dependence, Spatial Aggregation Bias, Spatial Sampling Bias.

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Edoardo Baldoni (*corresponding author)
Department of Economics and Social Sciences, Università Politecnica delle Marche, Ancona, Italy
Address: Piazzale Martelli 8, 60121, Ancona, Italy
Email: edoardo.baldoni at gmail.com
Phone: +39 329 951 6992

Roberto Esposti
Department of Economics and Social Sciences, Università Politecnica delle Marche, Ancona, Italy
Address: Piazzale Martelli 8, 60121, Ancona, Italy
Email: r.esposti at univpm.it
Phone: +39 071 2207119
Fax: +39 071 2207102

This article concerns modeling and estimation of the spatial dependence of agricultural Total Factor Productivity (TFP). The objective of the present work is twofold. On the one hand, it aims to put forward a modelling approach that is able to provide a comprehensive representation of spatial dependence of agricultural productivity (Holloway, Lacombe and Shaughnessy 2014): its sign and magnitude (*the scale*); the extent of its geographical range or width (*the scope*); its underlying causes, i.e. either actual production externalities or the presence of common localized production fundamentals (*the nature*) (Greenstone, Hornbeck and Moretti 2010; Ahlfeldt et al. 2014). On the other hand, it addresses some fundamental statistical issues of modeling spatial phenomena with survey data.

The proposed empirical approach consists in three steps. Firstly, a transitive TFP index is computed on farm-level output and input data adapting the method proposed by Hill (1999; 2004). Secondly, these farm-level output and input data are aggregated at an appropriate geographical scale to obtain an aggregate measure of TFP. This appropriate aggregation level is identified through Bayesian model selection procedures. Thirdly, TFP dependence across time and, above all, space is investigated on aggregate data by estimating a dynamic spatial panel model that makes all possible sources of productivity differentials explicit. Alternative specifications and estimators are also confronted.

The application concerns Italian FADN (Farm Accountancy Data Network) farm-level data over the period 2008-2015. Model estimates are then used to describe the main features of the productivity diffusion process in Italy.

Agricultural productivity across space: dependence and aggregation issues

The sources of productivity spatial dependence: production fundamentals and spillovers

Agricultural technology is often transmitted in the form of inter-sectoral and inter-regional spillovers (Alfranca and Huffman 2003; Huffman and Evenson 2001). This technology diffusion is expected to minimize and progressively close the productivity differentials across space. Nonetheless, the empirical literature (Hayami and Ruttan 1970; Ball 1985; Maietta and Viganò 1995; Acquaye, Alston and Pardey 2002; Pierani 2009; Sheng et al. 2014) has highlighted large cross-country and cross-region productivity differentials and would rather suggest that such a gap may be, at least partially, permanent. To reconcile these two facts, it is usually concluded that these differentials are the consequence of the site-specificity of agricultural productivity.

Transmission and site-specificity empirically express their magnitude in the form of productivity spatial dependence. The existence, magnitude and width of this spatial dependence has attracted much attention in empirical studies (Acquaye, Alston and Pardey 2002). In fact, it can be stated that spatial productivity dependence is the eventual outcome of two different determinants, *production fundamentals* and *productivity spillovers*.

Agricultural production fundamentals refer to “any characteristic of a location that directly affects productivity independently of the surrounding economic activity” (Ahlfeldt et al. 2015, p. 2128; Acemoglu and Zilibotti 2001). These fundamentals consist in localized unchangeable, irreproducible and non-transferable environmental - both ecological or socio-historical - factors. Productivity externalities concern the effect generated by any single i-th production unit on the productivity of the neighboring units. The main economic force generating this positive externality is the diffusion of technology and knowledge and the consequent adoption and adaptation of innovations (Ellahi, Fleming and Villano 2010; Läpple et al. 2017). These externalities tend to be localized not only because geographical proximity facilitates diffusion, but also because agricultural technology itself is spatially specific and tailored on localized farming systems (Larue, Abildrup and Schmitt 2011, Läpple et al. 2017).

The separation of production fundamentals from productivity externalities requires an appropriate modeling framework and is empirically challenging (Brueckner 2003). This represents one of the main objectives of this work.

Agricultural productivity and the spatial aggregation dilemma

The investigation of spatial dependence of productivity is critically influenced by the spatial scale of investigation. The appropriateness of this scale depends on two contrasting sources of bias, here referred to as the *spatial sampling bias* and the *spatial aggregation bias*.

The *spatial sampling bias* refers to two main problems associated with the use of micro data in spatial econometrics (Chakir and Lungarska 2017).[1] The first issue is that, to fully model interactions across spatial units at the micro level, the available dataset should contain the full population of farms (Anselin 2001; Anselin 2002; Brueckner 2003) and their location should be free from errors or uncertainties (Arbia, Espa and Giuliani 2015). In practice, however, farm-level data are normally collected through surveys and inevitably suffer imperfections due to the sampling scheme, missing responses and to other data collection issues (Boehmke, Schilling and Hayes 2015). As stressed by Arbia, Espa and Giuliani (2015), such imperfections are not just incidental to the statistical analysis, but they can mask and hide the real phenomena up to the point of dramatically distorting inferential conclusions. Secondly, the identification and estimation of complex spatial dependence can be empirically unfeasible within very large micro panels unless major, and questionable, assumptions are made (Cardamone 2014; Baltagi, Egger and Kesina 2016). In practice, investigating spatial dependence with micro data may often be unviable or unreliable.

Because of the issues that affect micro level analyses, it seems reasonable to turn to aggregate data that, due to their lattice structure, should not suffer from spatial gaps. However, even aggregate spatial analyses are not exempt from statistical issues as they may suffer from a *spatial aggregation bias*. This bias can be described as the combination of two related issues: ecological fallacy and Modifiable Unit Areal Problem (MUAP) (Anselin 2002).

Ecological fallacy arises whenever findings at the macro level are transferred to the micro level, and it is problematic because, unless rigid homogeneity constraints are imposed, micro phenomena are intrinsically different from macro phenomena (Anselin 2002; Liu and Shumway 2004). This seems particularly evident in the case of agriculture where the complex linkages among farms are typically local and highly affected by structural and production similarity. At an aggregate level, such complexity vanishes. Moreover, aggregate units may generate a "gravity" impact on neighbours for which there is no correspondence at the micro level. Ultimately, farm-level and aggregate productivity may be rather different things. While farm-level productivity may heavily depend on size and output structure, and on the neighbours' similarity, aggregate productivity manifests this heterogeneity in the form of a composition effect that eventually may affect spatial dependence. The difference between productivity at the micro and at the macro level is larger the larger is the scale of data aggregation. The MUAP is an additional, related issue that concerns how aggregation of spatial units is performed. In fact, the choice of both shape and scale of spatial units/polygons may have important consequences on statistical inference (Holt et al. 1996; Wakefield and Lyons 2010).

The spatial sampling bias and the spatial aggregation bias generate a dilemma on the most appropriate level of investigation. However, as it seems difficult to address the spatial sampling bias due to, essentially, lack of information, an appropriate empirical strategy can help minimizing the spatial aggregation bias.

In this work, we aim to model spatial dependence at an aggregate level but, in a first step, evidence from farm-level data is used to guide the choice of the most appropriate aggregation level so to minimize this spatial aggregation bias. We claim that by choosing a granular-enough aggregation level, this bias can be minimized and the spatial properties of TFP at the micro level recovered.

To prove it in the context of the present modeling framework, a simulation exercise can be helpful and is here performed. Results of this exercise are presented in Appendix A. This exercise consists in simulating a space-time stochastic process at the micro level and then estimating iteratively spatial dependence using models with aggregate data. Alternative artificial square grids with an increasing side length are used to aggregate the simulated micro data and to illustrate how geographical aggregation may generate a bias in the estimation of spatial dependence. It emerges that only using a granular-enough aggregation level micro-level properties of spatial dependence can be preserved.

Modelling productivity dependence within a panel

The theoretical framework

One of the key methodological challenge of the present study consists in empirically separating production fundamentals from productivity spillovers. This separation requires an appropriate modelling of the stochastic process of agricultural productivity.

Consider a panel of *N* production units observed over *T* periods and represent the unit-specific production technology with the following generic neoclassical production function (Chambers 1988):

(1) $Y_{it} = F^{i}\left(K_{it}, L_{it}, t\right), \;\; i = 1, \dots, N; \; t = \; 1, \dots, T$

where Y represents the aggregate output while L and K are labour and capital inputs (with K aggregating, for simplicity, all the non-labour production factors), and *t* is the usual time trend proxying the unobserved level of the technology. By assuming disembodied exogenous technological change, (1) can be rewritten as (Solow 1956; Chang 1970; Hulten 1992):

(2) $Y_{it} = A_{t}F^{i}\left(K_{it}, L_{it}\right)$

A_{it} is a measure of i-th unit´s Hicks-neutral productivity (TFP) in time period *t*. It represents all unobserved determinants of output, typically measured as the production function residual (Solow 1956). By differentiating (2) over time (Chang 1970; Hulten 1992) we obtain the following expression:

(3) $\dot{A}_{it} = \dot{Y}_{it} - \theta_{kit}\dot{K}_{it} - \theta_{kit}\dot{L}_{it}$

where $\dot{A}_{it}, \dot{Y}_{it}, \dot{K}_{it}, \dot{L}_{it}$ express the growth rates of *A*, *Y*, *K* and *L*, respectively. θ_{kit} and θ_{kit} denote output elasticities of capital (*K*) and labour (L). Under profit maximization, competitive input markets and constant returns to scale, θ_{kit} and θ_{Lit} correspond to the respective factor shares.[2]

Although not directly observable, $\ln A_{it}$ - or analogously $\ln TFP_{it}$ - can be measured through index number techniques (Coelli et al. 2005; Fried, Lovell and Schmidt 2008, Fuglie 2012; Fuglie 2015). By reformulating (3) in discrete-time, and by taking two contiguous observations, *t* and *t*-1, (3) can be rewritten as:[3]

(4) $(\ln TFP_{it} - \ln TFP_{it-1}) = (\ln Y_{it} - \ln Y_{it-1}) - \left[\left(1 - \frac{q_{Lit}+q_{Lit-1}}{2}\right)(\ln K_{it} - \ln K_{it-1}) + \left(\frac{q_{Lit}+q_{Lit-1}}{2}\right)(\ln L_{it} - \ln L_{it-1})\right]$

where q_{Lit} and q_{Lit-1} are the observed labour shares in the two observations. The terms in square brackets of (4) are discrete-time (Theil-Tornqvist) approximations of Divisia input indexes (Chambers 1988, p. 233).[4] The left-hand side of equation (4) can be regarded as a conventional TFP index of a generic observation compared to a reference observation.

Productivity determinants

Once properly measured, TFP differentials within a panel can be investigated by distinguishing observed and unobserved productivity determinants. Following Eberhardt and Helmers (2010), the i-th unit productivity performance at time *t* can be expressed as the following combination of terms:

(5) $\ln TFP_{it} = \mu_0 + \mu_t + \mu_i + \mu_{it} + \mathbf{Z}_i\boldsymbol{\alpha} + \mathbf{X}_{it}\boldsymbol{\beta}$

where μ_0, μ_t, μ_i and μ_{it} are unobserved determinants: μ_0 represents the mean productivity across firms and over time; μ_t the t-th time specific productivity common to all units; μ_i the i-th unit time-invariant specific productivity; μ_{it} the i-th unit time-variant specific productivity. $\mathbf{Z}_i$ and $\mathbf{X}_{it}$ are (1xk) and (1xh) vectors of time invariant and time-variant observable productivity determinants, respectively, and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the correspondent (kx1) and (hx1) vectors of unknown parameters to be estimated.

Term μ_{it} is unobserved by the econometrician but it is known to the producer. So, from the econometrician's perspective it simply represents a component of the error term while for the farmer it is available information that affects its decisions on inputs usage. Therefore, inputs in production functions are partially determined by unobserved time-variant characteristics contained in μ_{it}. The usual exogeneity assumptions are thus unlikely to hold (Marschak and Andrews 1944; Mundlak 1961; Griliches and Mairesse 1995).

A solution to this endogeneity problem consists in specifying the dynamic stochastic process eventually generating μ_{it}. Here, we extend the Blundell and Bond (2000) approach admitting both productivity dynamics and space dependence, that is by specifying μ_{it} as a spatial AR(1) process:

(6) $\mu_{it} = \rho\mu_{it-1} + \delta\mathbf{W}\,\mu_{it} + \varepsilon_{it}$

where μ_{it} is the (NTx1) vector of the time-variant productivity (μ_{it}) and ε_{it} is an i.i.d. ~$N(0,\sigma^2)$ error term component representing unexpected deviations from the mean due to measurement errors, unexpected delays or other external circumstances (Van Beveren 2010). $\mathbf{W}$ is the NxN spatial weights matrix, expressing the degree of contiguity of any i-th unit with the surrounding space.

From a farm-level perspective, the introduction of autocorrelation and the spatial lag in (6) can be given an explicit theoretical interpretation and justification. Autocorrelation aims to capture the delayed response of producers to changes in productivity. This delay occurs because input decisions are subject to hiring/investment costs generating rigidities (Slade 1988; Esposti 2000; Esposti 2011).[5] The spatial lag is aimed to capture the spatial dependence of productivity generated by productivity spillovers.

By substituting (6) into (5) and rearranging in compact vector notation we obtain:

(7) $\mathbf{lnTFP}_t = \overline{\mu_0}\boldsymbol{I}_N + \bar{\mu}_t\boldsymbol{I}_N + \rho\mathbf{lnTFP}_{t-1} + \delta\mathbf{WlnTFP}_t + \bar{\rho}\boldsymbol{\mu} - \delta\mathbf{W}\boldsymbol{\mu} + \mathbf{Z}\boldsymbol{\alpha} + \mathbf{WZ}\bar{\boldsymbol{\alpha}} + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{WX}_t\bar{\boldsymbol{\beta}} + \mathbf{X}_{t-1}\bar{\bar{\boldsymbol{\beta}}} + \boldsymbol{\varepsilon}_t$

where: $\boldsymbol{I}_N$ is the Nx1 identity vector; $\boldsymbol{\mu}$ is the Nx1 of the time-invariant unit-specific productivity μ_i; $\mathbf{lnTFP}_t$ is the Nx1 vector of time t productivity levels; $\mathbf{Z}$ and $\mathbf{X}_t$ are the Nxk and Nxh matrices of time-invariant and time-variant observable productivity determinants, respectively. Coefficients in (7) are defined as follows: $\overline{\mu_0} = (1-\rho-\delta)\mu_0$, $\bar{\mu}_t = (1-\delta)\mu_t - \rho\mu_{t-1}$, $\bar{\rho} = (1-\rho)$, $\bar{\boldsymbol{\alpha}} = -\delta\boldsymbol{\alpha}$, $\bar{\boldsymbol{\beta}} = -\delta\boldsymbol{\beta}$, $\bar{\bar{\boldsymbol{\beta}}} = -\rho\boldsymbol{\beta}$. Here, ρ and δ are the two unknown autoregressive coefficients, $\boldsymbol{\alpha}$ and $\bar{\boldsymbol{\alpha}}$ are the two *Kx1* vectors of unknown coefficients associated with the exogenous time-invariant variables $\mathbf{Z}$ and $\boldsymbol{\beta}$, $\bar{\boldsymbol{\beta}}$, $\bar{\bar{\boldsymbol{\beta}}}$ are Mx1 vectors of unknown coefficients associated with the exogenous time-variant variables contained in $\mathbf{X}$. $\boldsymbol{\varepsilon}_t$ is the Nx1 vector of error terms assumed to be i.i.d. $\sim N(\mathbf{0},\sigma^2\mathbf{I})$.[6]

Estimable Dynamic Spatial Panel (DSP) model

Identification of equation (7) is challenging. There are too many simultaneous effects to be able to identify and distinguish from each other the various spatial effects discussed in previous sections. Therefore, in order to achieve this, some terms of (7) must be excluded or restricted. In particular, it seems reasonable to assume that the time-invariant unobserved and observed determinants, i.e. terms μ_i and $\mathbf{Z}_i$ in (7), behave exclusively as production fundamentals: they affect productivity performance of the i-th unit, but they do not affect the productivity of the surrounding space if not, indirectly, through the spatially lagged TFP.

In this respect, in (7) the role of the time-variant observable productivity determinants, $\mathbf{X}_t$, is essential as they make clear how the theoretical distinction between production fundamentals and production spillovers can be empirically unviable. This occurs because, even though $\mathbf{X}_t$ includes trans-temporal shocks on agricultural productivity, they can still be highly location-specific. Environmental variables typically are spatially determined but are also source of temporary shocks (for instance, weather conditions). Therefore, production fundamentals (i.e., those productivity determinants that should not generate productivity spillovers) can be expressed by both $\mathbf{Z}$ and $\mathbf{X}_t$, not only by $\mathbf{Z}$. At the same time, however, (7) admits that temporary shocks in $\mathbf{X}_t$ may be directly transmitted across space (via term $\mathbf{W}\mathbf{X}_t\bar{\boldsymbol{\beta}}$). This seems reasonable since, as these shocks may be location specific, they may also diffuse over space (the typical example, again, can be the effects of extreme weather conditions). The consequence is that variables in $\mathbf{X}_t$ can incorporate productivity funtamentals that generate, at the same time, productivity spillovers.

This assumption allows (7) to be simplified as follows:

(8) $$\mathbf{lnTFP}_t = \overline{\mu_0}\boldsymbol{I}_N + \bar{\mu}_{\mathrm{t}}\boldsymbol{I}_N + \rho\mathbf{lnTFP}_{t-1} + \delta\mathbf{WlnTFP}_t + \bar{\boldsymbol{\mu}} + \mathbf{Z}\boldsymbol{\alpha} + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\bar{\boldsymbol{\beta}} + \mathbf{X}_{t-1}\bar{\bar{\boldsymbol{\beta}}} + \boldsymbol{\varepsilon}_t$$

where $\bar{\boldsymbol{\mu}} = \bar{\rho}\boldsymbol{\mu}$.

Equation (8) can be considered a simplified version of the so-called *Dynamic Spatial Durbin Model* (DSDM) with spatial fixed effects ($\bar{\boldsymbol{\mu}}$) and will be denominated as such henceforth (Elhorst, 2014).[7] The estimation of the DSDM provides evidence on the main objective here, i.e., scale, scope and nature of the spatial dependence of agricultural productivity.

Consequently, in (8) spatial dependence may originate when neighboring units share common or similar time-invariant and/or time-variant fundamentals, that is from $E\left[Z_i Z_j\right] \neq 0$ and/or $E\left[X_{it} X_{jt}\right] \neq 0$. Due to time-invariance, the former correlation does not generate productivity spillovers. The latter correlation, on the contrary, may affect productivity in the neighbouring space both directly through term $\mathbf{W}\mathbf{X}_t\bar{\boldsymbol{\beta}}$ (exogenous spillovers) and indirectly through term $\delta\mathbf{W}\mathbf{lnTFP}_t$ (endogenous spillovers). Therefore, in (8) productivity spillovers and production fundamentals are not entirely separate as $\mathbf{X}_t$ may imply both effects. Nonetheless, estimation of model coefficients may lead to the separation of these production fundamentals (through coefficients $\boldsymbol{\beta}$ and $\bar{\bar{\boldsymbol{\beta}}}$) from the effects of exogenous productivity spillovers (through matrix $\mathbf{W}$ and coefficients $\bar{\boldsymbol{\beta}}$).

Alternative specifications

Though empirically feasible and highly informative, the DSDM remains computationally demanding and may contain redundant parameters (Anselin, Le Gallo and Jayet 2008). In fact, the representation of the productivity transmission across space can be achieved through simpler specifications. In particular, one of the following two simplified specifications can be considered (LeSage and Pace 2009; Elhorst 2010a; Camaioni et al. 2016).[8] The first is the so-called Dynamic Spatial Lag Model (DSLM) with fixed effects (Debarsy, Ertur and LeSage 2012) that admits only an endogenous spatial interaction:

(9) $$\mathbf{lnTFP}_t = \overline{\mu_0}\boldsymbol{I}_N + \bar{\mu}_{\mathrm{t}}\boldsymbol{I}_N + \rho\mathbf{lnTFP}_{t-1} + \delta\mathbf{W}\mathbf{lnTFP}_t + \bar{\rho}\boldsymbol{\mu} + \mathbf{Z}\boldsymbol{\alpha} + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{X}_{t-1}\bar{\bar{\boldsymbol{\beta}}} + \boldsymbol{\varepsilon}_t$$

In practice, the assumption is that the common production fundamentals contained in $\mathbf{X}_t$ express features of the cross-sectional units for which no diffusion process can be conjectured. In other words, the separability issue between production fundamentals and spillovers is here solved by assuming that no exogenous productivity spillovers occur (as term $\mathbf{W}\mathbf{X}_t\bar{\boldsymbol{\beta}}$ is removed) and variables $\mathbf{X}_t$ may possibly express only production fundamentals.

The second specification, the so-called Dynamic Spatial Lag of X (DSLX) model with fixed effects, only admits an exogenous spatial interaction (i.e., exogenous spillovers through $\mathbf{W}\mathbf{X}_t\bar{\boldsymbol{\beta}}$):

(10) $$\mathbf{lnTFP}_t = \overline{\mu_0}\boldsymbol{I}_N + \bar{\mu}_{\mathrm{t}}\boldsymbol{I}_N + \rho\mathbf{lnTFP}_{t-1} + \bar{\rho}\boldsymbol{\mu} + \mathbf{Z}\boldsymbol{\alpha} + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\bar{\boldsymbol{\beta}} + \mathbf{X}_{t-1}\bar{\bar{\boldsymbol{\beta}}} + \boldsymbol{\varepsilon}_t$$

In this case, endogenous productivity spillovers are assumed to be zero and productivity dependence may be observed, beside variables $\mathbf{Z}$, because the trans-temporal shocks expressed by time-variant $\mathbf{X}_t$ diffuse across space and generate a common response of the TFP.[9] Whether or not it is preferable to move from the DSDM to one of these two simplified versions is evidently an empirical question that requires appropriate model selection procedures in the estimation stage.

Data, aggregation levels and productivity indexes

The micro and the macro panels: from farms to regions

The illustrative empirical application of the proposed approach uses the farm-level survey data provided by the Italian Farm Accountancy Data Network (FADN) and covers the period 2008-2015. Each year, the survey consists of an unbalanced panel of around 11,000 commercial farms. The FADN sample is only a small fraction of the universe of commercial farms in Italy. Therefore, analyzing spatial dependence at the micro level may incur spatial sampling bias. Moreover, the unbalanced nature of the panel poses serious estimation issues due to large, time-varying spatial weights matrices[10]. In fact, this unbalanced panel should not be used to estimate model (8), or its variants (9) and (10). Instead, a possible use of this farm-level dataset consists in extracting the balanced panel of 2,409 farms (N=2,409 and T=8, i.e. 19,272 observations) in order to inspect some of the spatial properties of TFP. Although it can exacerbate the spatial sampling bias due to additional spatial gaps, estimating model variants (8)-(10) on the balanced panel is feasible and avoids complex estimation issues. The estimation of the scale and nature of productivity spatial dependence at this micro-level can be potentially misleading. However, as shown with the simulation exercise detailed in Appendix A, it can still be helpful here as pilot evidence to identify the geographical scope of this dependence, that is, to steer the choice of the appropriate aggregation level at which the conclusive model estimation is performed.

Among the possible alternative administrative levels, the Italian NUTS3 regions emerge as a suitable aggregation level. This macro dataset consists of a balanced panel of 106 Italian NUTS3 regions[11] (N=106 and T=8, i.e. 848 observations). In order to form this macro panel, the full FADN unbalanced sample is aggregated at this geographical level at which model variants (8)-(10) are estimated for the estimation of spatial dependence.[12]

The Multilateral TFP (MTFP) index

Productivity measurements for the two panels are obtained with a multilateral (transitive) TFP (MTFP) index following the Hick-Moorsteen (HM) approach (Coelli et al. 2005; Fried, Lovell and Schmidt 2008). The HM index is constructed as the ratio of a transitive Fisher output quantity index to a transitive Fisher input quantity index. Because the usual Fisher index might not satisfy the transitivity property - i.e., a direct comparison between two farms is equal to the indirect comparisons of the two through a third one, so the rank of the index is independent from the unit and the time chosen as basis - a transitivization method called *Minimum Spanning Tree* (MST) is used here. This method requires the selection of a set of bilateral comparisons to be chained together in a spanning tree.[13] The set of bilateral comparisons is established through a specific procedure that identifies the best pairs of units (farms or regions) based on the similarity of their prices and quantities. The spanning tree is identified as the one that minimizes the global distance between the nodes of the tree where distances are defined as the Paasche-Laspeyres Spreads (PLS) (Hill 1999; Hill 2004). Following this methodology, aggregate transitive output and input indexes are computed for any spatial unit in any time period. The information available in the FADN for the construction of input and output indexes is quite rich. On the input side, the following factors have been included: labor, capital services, land, fertilizers, pesticides, external services, water, electricity, seeds, feeding stuff, reuses and other general expenses. On the output side, output quantities and implicit prices of the large number of crop and livestock products have been used. To limit the dimensionality of output vectors, the least relevant products in terms of production value have been aggregated together resulting in a final vector of 346 output items. Regional-level prices are obtained as production-weighted average prices.

Table 1 compares MTFP (mean and median MTFP level) within the micro panel and across alternative spatial aggregations (included the NUTS3 level). In the micro panel, statistics are based on the farm-level MTFP indexes and then calculated on alternative sub-sets of farms (by macroregion, altitude class, size and specialization). On the contrary, the aggregate statistics are computed by firstly constructing the MTFP indexes at the respective aggregation levels instead. This multidimensional description of agricultural productivity performance would not be possible without the availability of farm-level data with the consequent flexibility of aggregation.

Table 1 shows that productivity differentials among Italian farms are large. This farm-level heterogeneity also motivates the difference between the mean and the median value suggesting an appreciably skewed MTFP distribution with a long right tail due to a small number of highly productive farms. Farm-level productivity differentials are mostly the consequence of different size and production specialization (MTP tends to be higher in larger farms and in farms specialized in dairy, horticulture and fruit production). As a consequence, the aggregate MTFP indexes inevitably show lower productivity heterogeneity as part of these farm-level differentials are neutralized with geographical aggregation.

To highlight significant geographical differentials, Figure 1 reports the average MTFP index and its average annual growth rate over the 2008-2015 period at the geographic scale of analysis finally adopted (NUTS3 regions). While some spatial patterns can be identified with clusters of regions showing similar performance, no clear North-South or East-West gradient can be detected.

Estimation

Estimation of model specifications (8)-(10) raises three major concerns. The first is the specification of matrix $\mathbf{W}$ expressing interactions between spatial units. The second issue concerns the inherent endogeneity of any dynamic space-time panel model (Blundell and Bond 1998; Arellano 2003; Roodman 2009) caused by both time-lagged and the space-lagged dependent variables. While the implications of the time-lagged term have been widely investigated in panel data econometrics (Arellano 2003), the literature about the latter is more recent. As detailed in Appendix B, the presence of endogenous terms in (8) and (10) implies autocorrelation of the disturbances across time and non-linearity in the parameters thus preventing a consistent estimation through OLS. The third estimation issue concerns the possible endogeneity of production fundamentals themselves ($\mathbf{X}_t$) (Ahlfeldt et al. 2015).

The spatial weights matrix

The *N*x*N* spatial matrix $\mathbf{W}$ is specified to express the proximity among units. When geographical units are considered, proximity depends on contiguity and distance. Therefore, neighbourhoods identified by radial distance augment a queen contiguity matrix: the i-th row/j-th column element is fixed at 1 if the j-th and i-th units are contiguous or the former falls within the pre-determined radial distance from the latter; at 0 otherwise.

However, proximity among units is not only a matter of space but it also involves production technology. Thus, the spatial matrix $\mathbf{W}$ is weighted to account also for technological proximity. The assumption is that the linkage between any pair of units is stronger the closer is their agricultural specialization. Each element w_{ij} of the spatial matrix $\mathbf{W}$ is weighted by a technological proximity index (tp_{ij}). tp_{ij} is measured as the inverse of the Euclidean distance of the vectors of Utilized Agricultural Area (UAA) shares by production specialization of regions i and j. This augmented spatial matrix is finally row-standardized before model estimation.

When the estimation is performed directly on the micro panel, $\mathbf{W}$ is specified only on the basis of the radial distance between farms, while tp_{ij} simply takes the value of 2 whenever farms i and j belong to the same farm typology (i.e. production specialization) and the value of 1 otherwise.

The exogenous and instrumental variables

A further specification issue concerns the selection of exogenous variables capturing productivity performance depending on common localized production fundamentals. First, terms $\boldsymbol{\mu}$ are included as conventional fixed effects to seize all unit-specific time-invariant components of production fundamentals.[14] Secondly, time dummies $\bar{\mu}_{\mathrm{t}}\boldsymbol{I}_N$ are included to control for common annual shocks across spatial units. Finally, three additional time-variant variables $\mathbf{X}_t$ enter the model: the occurrence of extreme weather events; the economic size of the farms; production specialization. The former is a dummy variable taking value 1 whenever for the i-th unit at time t the annual precipitation is 36% higher than the respective long-term average. Economic size aims to capture the possible presence of non-constant returns to scale in agricultural production and that can affect the usual index-number TFP measurement. It is expressed by the average farm-level Standard Output.[15] Production specialization is, in fact, entered as a set of variables expressing the yearly percentage of Standard Output by group of products (see Table 1).[16]

One major issue is the possible endogeneity of these variables $\mathbf{X}_t$. In (8)-(10) the assumption $E[\mathbf{X}_{it}\ln TFP_{it}] = 0$, thus $E[\mathbf{X}_{it}\varepsilon_{it}] = 0, \forall i, t$ can be questionable. It cannot be excluded that i-th unit productivity performance depends on the producer's decisions eventually expressed in $\mathbf{X}_{it}$ that, in turn, may depend on the productivity performance. This argument can be even more relevant for the past productivity performance, i.e., $E[\mathbf{X}_{it}\ln TFP_{it-1}] = 0$. As $\ln TFP_{it-1}$ is typically endogenous in panel models, $E[\mathbf{X}_{it}\ln TFP_{it-1}] \neq 0$ makes $\mathbf{X}_{it}$ itself endogenous (Villoria 2019).

While endogeneity can be obviously excluded for the extreme weather events, size and production specialization can reasonably incur the abovementioned endogeneity problem, as it may depend on the time *t* productivity performance itself. Therefore, when estimating (8)-(10), these variables have been instrumented with their time lags.

Alternative estimators

As surveyed by Elhorst (2010b; 2014), alternative estimators of DSP models have been proposed in order to deal with endogeneity issues. Four different estimators of model specifications (8)-(10) are used here.

The first is the Bias Corrected Maximum Likelihood (BCML) estimation that can be considered an extension to the DSP models of the Bias Corrected Least Square with Dummy Variables (BCLSDV) estimator of static panel models (Yu et al. 2008). Under a stationary dependent variable, this estimator is consistent for $N\to\infty$, $T\to\infty$ and $N/T\to\infty$, but its small sample performance, especially for T small, remains questionable.[17] A second estimation consists in extending to the DSP specification the usual dynamic panel GMM estimation approach (Arellano 2003). However, GMM estimation can be computationally demanding and, despite the desirable asymptotic properties, the small sample performance can be unsatisfactory.

The third estimation approach mixes the BCML estimation of the spatial correlation parameter δ with the unconditional ML estimation of the remaining parameters given the estimated δ (Elhorst 2010b). Under the stationarity of the dependent variable, this Mixed ML (MML) estimation outperforms BCML and GMM estimations when T is small. On the contrary, when T is small but stationarity is not granted, the GMM estimation should be preferred. The fourth estimator is the Integrated Nested Laplace Approximation (INLA) Bayesian approach that represents a computational alternative to the Bayesian MCMC method recently proposed by Elhorst (2014). Though it is very helpful when looking for the best model specification to be estimated (see below), its actual advantage compared to the alternative estimators is still questionable particularly with small T.

Bayesian model selection and aggregation levels

Before proceeding with model estimation, the empirical strategy proposed here looks for the most suitable aggregation level to seize spatial dependence while minimizing the spatial aggregation bias. By combining farm-level and macro-level data, this search is carried out through Bayesian model selection applied on alternative specifications of the spatial weights matrix and on the three alternative spatial specifications (8)-(10).

Bayesian inference has the main advantage of providing a natural solution to the problem of selecting the proper matrix **W** and is increasingly suggested by the recent literature on this topic (LeSage and Pace 2009; Elhorst 2010b; Elhorst 2014). The most widely used approach is the Bayesian Markov Chain Monte Carlo (MCMC) method (Elhorst 2014), but it is very computationally demanding particularly when performed on a micro panel as in the present case (LeSage, Chih and Vance 2019). To reduce the computational burden, the INLA Bayesian estimation approach is adopted (Lindgren and Rue 2015).[18]

This Bayesian model selection starts with a matrix **W** defined on a radial distance of 40 km. Then, **W** is iteratively redefined increasing this distance by 10 Km per iteration up to a maximum of 180 Km. The exercise is repeated for the three model specifications (8)-(10). Eventually, the highest posterior probability indicates the best model specification. This model selection procedure is firstly applied to the micro panel. Although, as discussed, at this aggregation level model estimation may suffer spatial sampling bias,[19] due to their high sampling density farm-level data are still very helpful here to identify the proper spatial scale of investigation.

Table 2 reports the results of this Bayesian INLA model selection. At the micro-level, the highest posterior probability is found with a radial distance of 100 Km and the DSLM specification. These results can be helpful to guide the selection of the most appropriate aggregation (macro panel) on which spatial dependence can be consistently estimated. In fact, the only Italian administrative level consistent with the selected radial distance are the NUTS3 regions. To confirm that the NUTS3 level is appropriate, the same Bayesian model selection procedure is carried out on data aggregated at the NUTS3 level. Posterior probabilities indicate the same radial distance (100 Km) and the same model specification (DSLM) identified with the micro panel. Therefore, in what follows model estimates will refer to the NUTS3 macro panel, a matrix **W** defined on a radial distance of 100 Km and the DSLM specification.[20]

Model estimation

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NUTS3 level estimates of the selected model specification (DSLM) with the selected **W** are presented in Table 3.[21] For the sake of comparison, estimation is performed with all the four abovementioned estimators.

The most relevant evidence concerns the substantial concordance of estimated coefficients across alternative estimators in terms of sign, magnitude and statistical significance. Moreover, all estimates respect the stability condition implied by spatial and time stationarity.[22] The observed positive sign of both time and spatial dependence confirms some persistence of productivity shocks over time and, more importantly, the presence of spatial productivity clusters. The magnitude of the spatial dependence is roughly between two and four times larger than temporal dependence. It appears to be statistically sound and rather stable (between 0.3 and 0.44) across estimators.

The statistical significance of estimated coefficients associated to the exogenous variables is limited. However, they move in the expected direction as the occurrence of extreme weather events tends to reduce the observed agricultural productivity while size increases it. In this latter case, the lack of conclusive evidence can be interpreted as a confirmation of a complex (i.e. not univocal) relationship between size and productivity in agricultural production already pointed out by previous studies (Sheng, Ding and Huang 2019).

The comparison across estimators does not reveal any conclusive superiority in terms of statistical quality. However, the spatial correlation coefficient is not statistically significant in the GMM estimation while the MML estimation is by far the most demanding in computational terms.[23] Therefore, in what follows the spatial diffusion of agricultural productivity is investigated further using the BCML estimates of the DSLM.

Agricultural productivity in space

As discussed in previous sections, model estimation allows for further and deeper evidence about the productivity diffusion process. Figure 2 displays the propagation across space of a simulated unit productivity shock in the NUTS3 of Parma (in black) at time *t* implied by model estimates. It emerges that, due to model stationarity and the limited size of the spatial autoregressive coefficient, significant direct effects are limited to neighboring regions while indirect effects tend to zero after the first two time periods. Figure 2 also illustrates how those regions that receive the largest effects from the original shock are those that are more similar in production structure to Parma. In fact, those NUTS3 associated to larger spillovers are those of Reggio Emilia and Modena but also the non-bordering NUTS3 of Bergamo whose technological contiguity is larger than geographically closer regions.

The effect of technological contiguity is represented also in the bottom panel of Figure 2. Assuming the same unit shock in Parma, it shows the cumulative spillovers in a cluster of neighboring regions far from the epicenter of the shock. The exercise is simulated in four NUTS3 regions in Campania over five time periods. By their cumulative spillover, it is shown that technology transfers depend on geographical distance but also on the similarity in production structure.[24]

The long-term implications of the estimated diffusion process of agricultural TFP in Italy are summarized graphically in Figure 3 using the set of spatial indicators presented in previous sections and detailed in Appendix B: long-term spillovers, spill-ins and absorption capacity. The long-term spillover is an indicator that shows the diffusion multiplier of each NUTS3 region, i.e., to what extent a shock is transferred from one region to the rest of the country in the long-term. Evidence suggests that central regions – in terms of geography and/or production structure – are those associated with higher spillover multipliers.

Spill-ins indicate how much each region receives when all others are shocked at the same time. It emerges that peripheral regions of the diffusion network (either geographically or technologically) are associated to lower spill-ins: high spill-ins can be observed in the core of the Italian agriculture and in the richest Italian regions. Still, for some regions their marginality implies an advantage in relative terms: when a productivity shock occurs, marginal regions receive more than what they give, and this relative gain is expressed by their higher absorption capacity. The opposite holds true for central regions and this would make them of primary interest for a policy intended to reduce productivity differentials within the national borders.

These additional elaborations on model estimates induce three major considerations on the productivity diffusion process. First, due to the limited scope and magnitude of spatial dependence, spillover effects of agricultural productivity are rather limited in space, at least in Italy. In fact, direct spillover effects are constrained within a radius of 100 km and spatial dependence is positive but limited in magnitude. Both evidences would suggest that technology transfers occur, but technology diffusion forces are limited to close neighborhoods. A second insight concerns the temporal dimension of diffusion. Due to limited persistence, any spillover effects tend to fade quickly over time. This evidence adds to the first in supporting the hypothesis that productivity shocks in agriculture are rather location specific. On top of these, a third important feature of the diffusion process concerns the production structure of spatial units. Due to the set-up of matrix **W**, similarity in production structure between NUTS3 regions matters in the diffusion of productivity shocks. Regions characterized by a similar production structure tend to transfer technology more than dissimilar ones.

Some concluding remarks

As farming is a strongly site-specific activity, agricultural productivity may substantially differ across space thus forming spatial clusters. The objective of the present article is to propose a methodological approach to investigate the spatial dependence of agricultural productivity and to identify how much of this dependence can be attributed to productivity spillovers. This approach not only makes the spatial dimension explicit and separates productivity spillovers from production fundamentals, but also operates over a small and flexible enough geographical scale to minimize the possible aggregation bias.

To achieve this, farm-level data are used to pursue the most appropriate scale at which spatial dependence can be investigated. At this scale a regional panel is constructed, and a dynamic panel model specified and estimated to identify all the possible sources of productivity differentials. The approach is illustrated with an application to an Italian farm-level panel sample. The NUTS3 regional level emerges as the most suitable aggregation level.

Results presented here suggest that at this scale the cost of aggregation is small as the information loss on spatial dependence and diffusion process is negligible. On the contrary, two main advantages of aggregation clearly emerge. On the one hand, computationally demanding estimation approaches can be more easily performed within macro panels. On the other hand, results obtained on macro panels are more geographically explicit and allow a more insightful representation and an interpretation (mostly through maps).

This latter aspect seems critical here because, the major interest of the approach eventually concerns the possible policy implications of the empirical evidence it generates. These implications can be more easily drawn whenever results are geographically explicit. As estimates confirm that agricultural productivity shocks diffuse across space, it follows that any policy affecting this process indirectly, and sometime unintentionally, also affects productivity differentials.

The relevance of these implications suggest caution in the interpretation of the results here obtained. They only apply to Italian agricultural and could be strongly specific. Therefore, their generalization would require the extension of the analysis to other contexts and cases. Moreover, further research effort is needed to improve the proposed approach especially with a finer representation of the spatial diffusion processes. Nonetheless, it remains true that a better understanding of the spatial character of agricultural productivity differentials and dynamics may eventually help to improve the design and targeting of agricultural policies, especially those aimed at knowledge and technology creation and diffusion.

Table 1. *Mean and Median MTFP within the Farm Sample and Across Different types of Aggregation.*

Aggregation levels	*NT*	*MTFP (mean)*	*MTFP (median)*
Micro panel:			
Whole sample *(N=2409, T=8)*	19272	4.958	2.245
Sub-samples:			
Macro-regions			
- North	2240	5.994	2.640
- Centre	11624	2.652	1.576
- South	5408	3.687	2.006
Altitude classes			
- Plains	6748	7.343	3.100
- Low-hillside	8236	3.283	1.629
- High-hillside	4288	4.422	2.619
Farm size			
- Small	3624	2.097	1.286
- Medium	9146	3.571	2.104
- Large	6502	8.505	3.848
Production specialization			
- Dairy	2205	5.144	3.796
- Cereals	2608	3.661	2.343
- Wine	2472	3.601	2.138
- Horticulture	2174	5.814	1.358
- Fruits	3035	10.562	4.207
- Arable crops	1860	3.831	1.753
- Granivores	590	3.143	0.784
- Olives	402	3.951	2.489
- Mixed	1738	2.694	1.647
- Grazing livestock	2188	3.143	1.423
Macro panels:			
NUTS3 regions (N=106, T=8)	848	2.101	1.556
Other Aggregation levels:			
Macro-regions			
- North	8	1.010	0.970
- Centre	8	0.935	0.902
- South	8	0.998	0.917
Altitude classes			
- Plains	8	1.138	1.092
- Low-hillside	8	0.881	0.856
- High-hillside	8	0.651	0.613
Farm size			
- Small	8	0.467	0.467
- Medium	8	0.925	0.925
- Large	8	1.219	1.219
Production specialization			
- Dairy	8	2.076	2.305
- Cereals	8	1.408	1.433
- Wine	8	1.757	1.721
- Horticulture	8	1.777	1.790
- Fruits	8	1.867	1.819
- Arable crops	8	1.574	1.558
- Granivores	8	0.608	0.529
- Olives	8	1.695	1.658
- Mixed	8	1.150	1.192
- Grazing livestock	8	0.764	0.756

Table 2. *Bayesian Posterior Model Probabilities of Alternative* **W** *Matrices and Model Specifications*

Model specification:	DSDM	DSLM	DSLX
W specification:			
Micro panel (farm level):			
Radial distance: 40 km	0.000	0.000	0.000
Radial distance: 50 km	0.000	0.000	0.000
Radial distance: 60 km	0.000	0.000	0.000
Radial distance: 70 Km	0.000	0.000	0.000
Radial distance: 80 km	0.000	0.000	0.000
Radial distance: 90 km	0.000	0.360	0.000
Radial distance: 100 km	0.000	**0.640**	0.000
Radial distance: 110 km	0.000	0.000	0.000
Radial distance: 120 km	0.000	0.000	0.000
Radial distance: 130 km	0.000	0.000	0.000
Radial distance: 140 km	0.000	0.000	0.000
Radial distance: 150 km	0.000	0.000	0.000
Radial distance: 160 km	0.000	0.000	0.000
Radial distance: 170 km	0.000	0.000	0.000
Radial distance: 180 km	0.000	0.000	0.000
Macro panel (NUTS3 regions):			
Radial distance: 40 km	0.000	0.000	0.000
Radial distance: 50 km	0.000	0.000	0.000
Radial distance: 60 km	0.000	0.000	0.000
Radial distance: 70 Km	0.000	0.000	0.000
Radial distance: 80 km	0.000	0.000	0.000
Radial distance: 90 km	0.000	0.000	0.000
Radial distance: 100 km	0.000	**1.000**	0.000
Radial distance: 110 km	0.000	0.000	0.000
Radial distance: 120 km	0.000	0.000	0.000
Radial distance: 130 km	0.000	0.000	0.000
Radial distance: 140 km	0.000	0.000	0.000
Radial distance: 150 km	0.000	0.000	0.000
Radial distance: 160 km	0.000	0.000	0.000
Radial distance: 170 km	0.000	0.000	0.000
Radial distance: 180 km	0.000	0.000	0.000

Table 3. *BCML, GMM, MML and Bayesian Estimates of the DSLM on Italian NUTS3 Regions. Spatial Matrix with 100 Km Radial Distance and Technological Contiguity – Standard Error in Parentheses*

Estimator: / Variable:	BCML	GMM-SYS	MML	Bayesian
(log TFP)$_{t-1}$	0.102** (0.046)	0.163*** (0.060)	0.089** (0.044)	0.102** (0.046)
W (log TFP)$_t$	0.442*** (0.047)	0.308 (0.460)	0.442*** (0.047)	0.442*** (0.074)
Extreme rainfall$_t$	-0.028 (0.107)	0.008 (0.123)	-0.037 (0.162)	-0.080 (0.121)
Extreme rainfall$_{t-1}$	-0.028 (0.106)	-0.008 (0.126)	-0.066 (0.132)	-0.047 (0.133)
Economic size$_t$	-0.159 (0.323)	-0.073 (0.107)	-0.058 (0.069)	0.064 (0.381)
Economic size$_{t-1}$	0.082 (0.074)	0.075 (0.098)	0.032 (0.054)	0.041 (0.089)
Production specializations	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	-	Yes

*,**,***: Statistically significant at the 10% and 5%, 1% level, respectively.

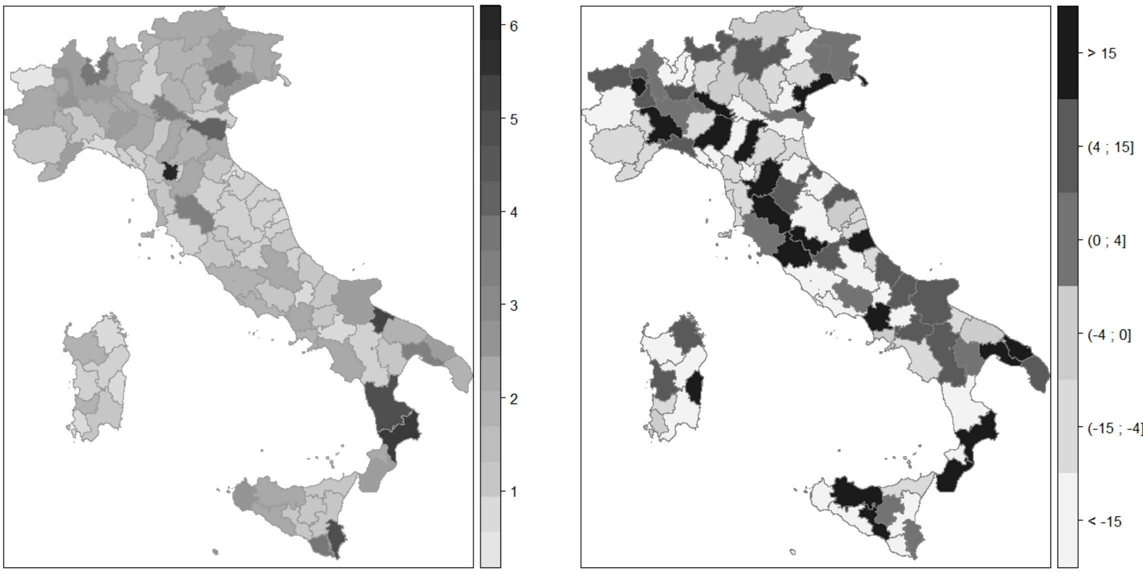

Figure 1. *Agricultural MTFP Index (2008-2015 Average) (left) and Average Annual MTFP Growth Rate (right) in Italian NUTS3 regions.* [a]

[a] Average MTFP index and growth rate in right axes

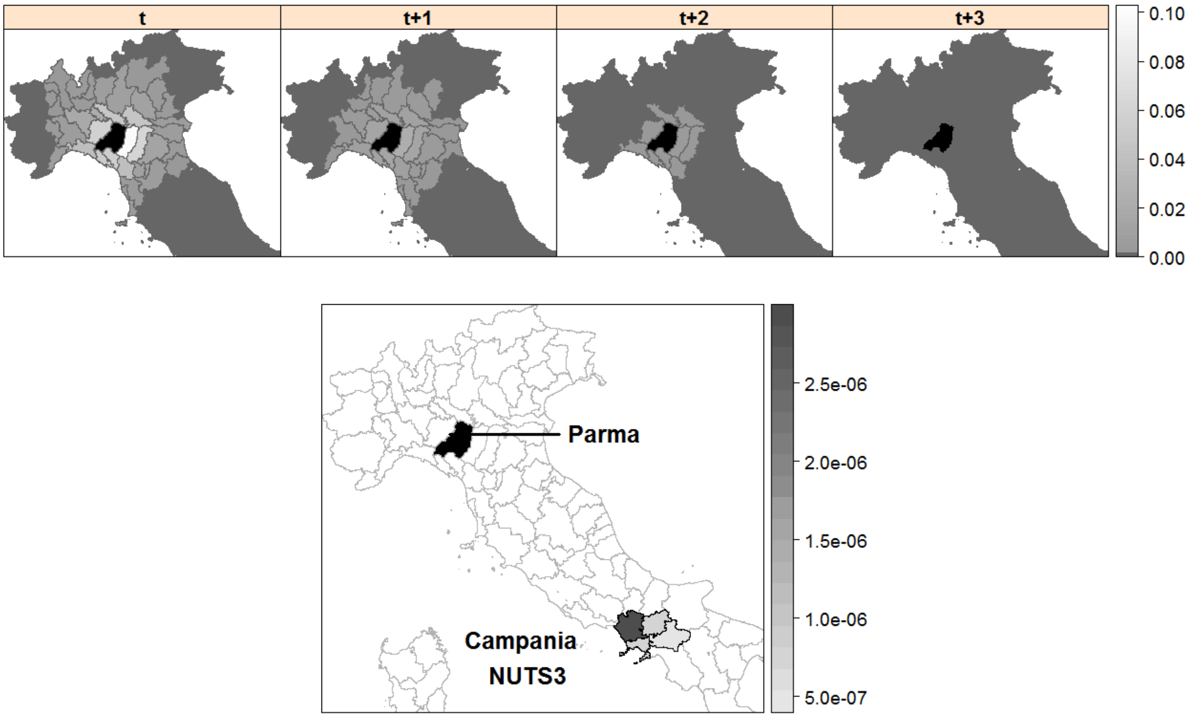

Figure 2. *Agricultural Productivity Contagion in Italian NUTS 3 Regions: Effects of a MTFP shock in Parma Province across Space and Over Time: top) Contemporaneous (t), After 1 Year (t+1), 2 Years (t+2) and 3 Years (t+3) Effect on the Neighboring NUTS3 Regions' MTFP; bottom) 5-year (t+5) Effect on Remote Regions (Campania Provinces).* [a]

[a] The right axis scale reports the TFP variation in response to a unit TFP shock (see Appendix B)

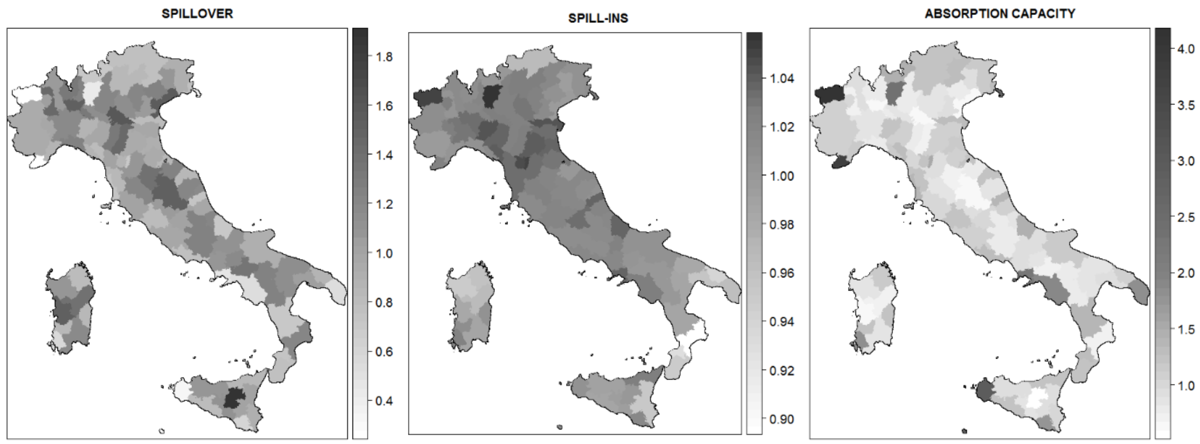

Figure 3. *Estimated Agricultural Productivity Spillover, Spill-ins and Absorption Capacity in Italian NUTS 3 Regions.* [a]

[a] The right axis scale reports the TFP variation in response to a unit TFP shock (see Appendix B)

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Appendix A: Simulation of spatial aggregation bias on artificial grids

A space-time stochastic process at the micro level is simulated by randomly sampling 200 coordinates pairs on the agricultural territory of Northern Italian regions. It is assumed that the process is characterized by a time-correlation coefficient of 0.1, a spatial-correlation coefficient of 0.4, a fixed-effect for any spatial units and a single exogenous variable whose associated coefficient is equal to 1.0. The assumed matrix **W** is a binary matrix with neighborhoods of 100 km radius. The process is simulated over 8 time periods. To illustrate how geographical aggregation may generate a bias in the estimation of spatial dependence, these micro data are averaged on four alternative square artificial grids (macro panels) of increasing size (Figure A1). For each aggregation, a fixed-effect Dynamic Spatial Lag Model (DSLM) with a single exogenous variable is iteratively estimated, via BCML estimation, over an increasing radial distance for **W**. The respective estimated spatial correlation coefficients (δ) are provided in Figure A2 for the four artificial grids. It emerges that using a granular-enough aggregation level (20 and 40 km side lengths), micro-level properties of spatial dependence (δ= 0.4 on a radial distance of km = 100) can be preserved while using larger spatial units (60 km and 100 km side lengths), aggregation makes the actual spatial dependence vanish in both size and, above all, statistical significance.

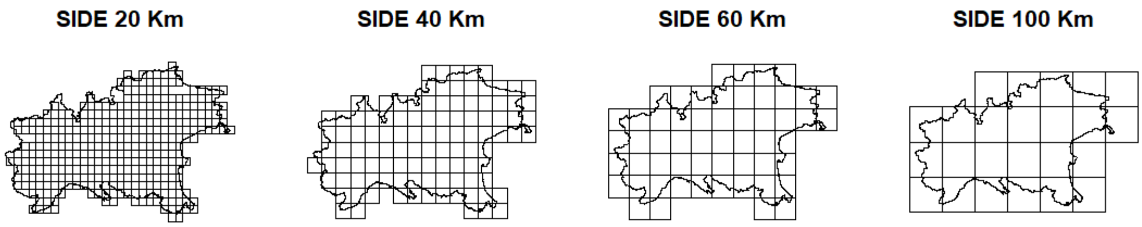

Figure A1. *The Four Artificial Squared Grids (Northern Italy) Adopted for the Simulation.* [a]
[a] Each grid is based on squared spatial units of increasing side-length

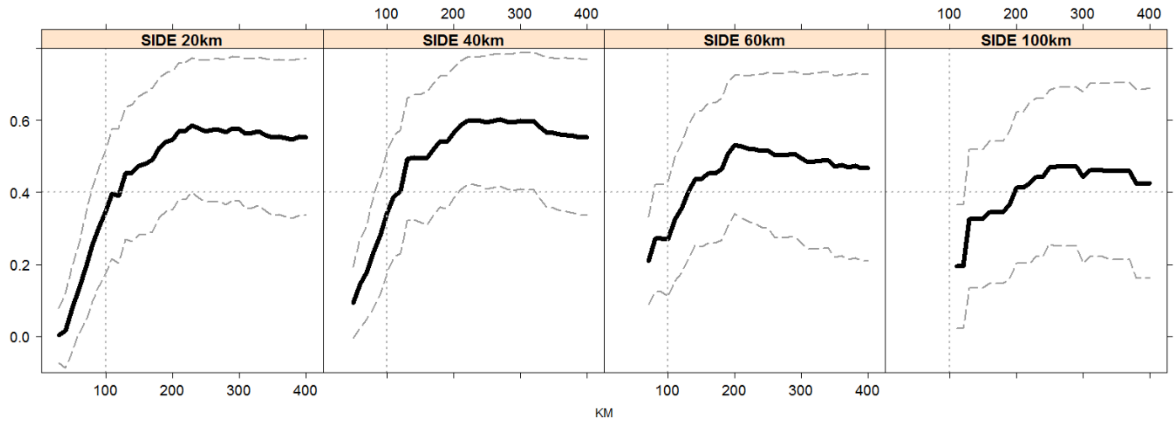

Figure A2. *Spatial Correlation Coefficient (vertical axis) Estimated on the Four Artificial Grids (Macro Panels) with Increasing Radius for **W** (Horizontal Axis, in Km) – 95% Confidence Intervals in Dashed Lines*

Appendix B: Disentangling Spatial Spillovers

The presence of time- and space-lagged dependent variable among regressors implies the following reduced form of (8):

$$\text{(B1)} \qquad \mathbf{lnTFP}_t = \left[\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right](\overline{\mu_0}\boldsymbol{I}_N + \bar{\mu}_{\mathrm{t}}\boldsymbol{I}_N + \bar{\boldsymbol{\mu}}) + \left[\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right]\mathbf{Z}\boldsymbol{\alpha} + \left[\left((1-\rho L)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right]\left(\mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\bar{\boldsymbol{\beta}} + \mathbf{X}_{t-1}\bar{\bar{\boldsymbol{\beta}}}\right) + \left[\left((1-\rho L)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right] + \boldsymbol{\varepsilon}_t$$

where L is the lag operator.

Productivity spillover is intended here as the time t effect on the i-th unit of a time t-s unitary productivity shock in the j-th unit, i.e. $\partial\mathrm{TFP}_{it}/\partial\mathrm{TFP}_{jt-s}, \forall i \neq j, \forall s = 0, \dots, T-1$. (A1) makes clear that spatial spillovers in (8) are expressed not only by the parameter δ (the *pure spatial effect*) but also by the complex feedbacks due to $\mathbf{W}$ and ρ. (B1) admits time and spatial dependence in a flexible enough way to allow differentiated short- and long-run effects as well as direct and indirect effects. These effects are heterogeneous across space.

Focusing on the long-run, three different effects can be computed from (B1) (Elhorst 2014, p. 105):[25]

- Long-term direct effects: $\left[\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right]^{d}$

These express the productivity impact, cumulated over time, on any i-th unit of a unitary TFP shock on the same unit at time t.

- Long-term indirect effects (*spill-ins*): $\left[\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right]^{rsum}$

These express the overall productivity impact, cumulated over time, on any i-th unit of a unitary TFP shock on all the other units at time t.

- Long-term indirect effects (*spillovers*): $\left[\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right]^{csum}$

$\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}$ is a NxN matrix whose superscripts d, $rsum$, $csum$ denote the respective Nx1 of diagonal elements, the Nx1 vector of the row sum of non-diagonal elements and the Nx1 vector of the column sum of non-diagonal elements. The ratio between the spill-ins and spillovers can be also computed. It is indicated here, for the sake of simplicity, as the *relative absorption capacity*, taking the form of the following Nx1 vector: $\frac{\left[\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right]^{rsum}}{\left[\left((1-\rho)\mathbf{I}-\delta\mathbf{W}\right)^{-1}\right]^{csum}}$.[26] Averaging over the N units it is also possible to express the mean spillovers, spill-ins and absorption capacity observed within the sample.[27]

These long-term effects express the overall productivity impact, cumulated over time, on all other spatial units of a unitary TFP shock on any i-th unit at time t. They depend on the fact that productivity spillovers necessarily take time, and this is even more true for the effects exceeding the neighboring space. As imitation and adoption might be long processes, these indicators are also able to assess the speed at which agricultural technology and innovations spread across space.

On the basis of these effects, the N spatial units can then be compared and ranked in order to identify those mostly generating and those mostly capturing productivity improvements. All these effects depend on the two unknown parameters to be estimated, δ and ρ, and on the structure of $\mathbf{W}$.

Comparing the restricted specifications (9) and (10) with (8), it is straightforward to derive the respective spillover effects. In (10) these effects entirely correspond with those obtained for (8). On the contrary, in (9) there are no spillover effects, since $\partial TFP_{it}/\partial TFP_{jt-s}$=0, and matrix **W** directly express how the shock on a time-variant production fundamental in the i-th unit may affect the productivity performance of the j-th unit, i.e. $\partial TFP_{it}/\partial X_{jt}$, $\forall i \neq j$.

Appendix C: Model estimates on farm-level data (micro panel)

Table C1. *BCML, GMM, MML and Bayesian estimates of the selected DSLM on farm-level data; Spatial matrix with 100 km radial distance and technological contiguity – Standard error in parentheses*

Variable: / Estimator:	BCML	GMM-SYS	Bayesian
$(\log \text{TFP})_{t-1}$	0.063*** (0.01)	0.209*** (0.038)	0.063*** (0.01)
$\mathbf{W}\ (\log \text{TFP})_{t}$	0.093 (0.070)	0.535*** (0.099)	0.093 (0.066)
Extreme rainfall $_{t}$	-0.004 (0.027)	0.03 (0.033)	0.043 (0.04)
Extreme rainfall $_{t-1}$	0.013 (0.023)	-0.053** (0.027)	0.008 (0.038)
Economic size $_{t}$	0.061 (0.129)	0.252*** (0.067)	0.053 (0.198)
Economic size $_{t-1}$	-0.02 (0.033)	-0.104* (0.054)	-0.025 (0.046)
Production specializations	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes

*,**,***: Statistically significant at the 10% and 5%, 1% level, respectively.

[1] The advantages and disadvantages of the spatial aggregation of farm-level data discussed here are parallel to the advantages and disadvantages of the micro-scale (farm-level) analysis discussed in Bell and Dalton (2007) and Bell and Irwin (2002).

[2] The assumption of constant returns to scale is not strictly needed within the adopted theoretical framework. However, the index number TFP calculation uses factor shares thus implicitly assumes constant returns to scale. Therefore, under non-constant returns to scale, the TFP calculation performed with index numbers also incorporates the impact of scale economies on productivity. The empirical implication of this issue are clarified later.

[3] Once units are ordered, contiguity can be also expressed in the cross-section dimension, i.e. between i-th and j-th units.

[4] In fact, the Divisia approach does not have a unique measurement of the TFP because the Theil-Tornqvist approximation is only one way to achieve a discrete-time approximation of left-hand terms of (4). Theil-Tornqvist indexes become exact discrete-time calculations of the respective Divisia indexes when the underlying production function is a Translog function, that is, a flexible functional form. There are other discrete-time approximations of the Divisia indexes that are exact for flexible functional forms (*superlative indexes*). Among superlative indexes, the Fisher ideal index is recommended for both economic and axiomatic criteria (Diewert 1992) and therefore, the Fisher index is used here.

[5] Within a neoclassical dynamic production function framework, Bond and Söderbom (2005) derive this autoregressive structure of the productivity term μ_{it} as the outcome of the intertemporal optimisation problem of the producer under stochastic adjustment costs associated to any modification of input levels.

[6] The normality assumption on this disturbance term implies that the dependent variable itself is assumed to be normally distributed. This assumption is clearly violated for the TFP level due to the strong asymmetry of the productivity performance within the sample as it ranges in the $[0,\infty)$ interval. For this same reason, however, its log-normal distribution over the $[0,\infty)$ support can be largely accepted. As TFP enters models (8)-(10) as logarithmic transformation, normality seems a reasonable assumption here.

[7] The proper specification of the DSDM is actually the following (Elhorst 2014) $\mathbf{lnTFP}_t = \overline{\mu_0}\boldsymbol{I}_N + \bar{\mu}_{\mathrm{t}}\boldsymbol{I}_N + \rho\mathbf{lnTFP}_{t-1} + \delta\mathbf{W}\ \mathbf{lnTFP}_t + \tau\ \mathbf{W}\ \mathbf{TFP}_{t-1} + \bar{\rho}\boldsymbol{\mu}\ + \mathbf{Z}\boldsymbol{\alpha} + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{WX}_t\bar{\boldsymbol{\beta}} + \mathbf{X}_{t-1}\bar{\bar{\boldsymbol{\beta}}} + \boldsymbol{\varepsilon}_t$. In the present case, the theoretical derivation of model (8) excludes the transmission across space of the lagged TFP. Nonetheless, (8) maintains the main characteristic of the DSDM, that is, it admits both exogenous (i.e. $\mathbf{WX}_t$) and the endogenous (i.e. $\mathbf{WlnTFP}_t$) spatial interaction. Therefore, the DSDM denomination is maintained here.

[8] As specifications (8)-(10) are restricted versions of (7), they also imply restrictions on the stochastic process generating the productivity term μ_{it} as represented in (6). By substituting backward, it is straightforward to derive the restrictions on (6) implied by specifications (8)-(10).

[9] For an application of the DSLX model to spatial spillovers see Crescenzi and Rodriguez-Pose (2012).

[10] While estimation of spatial panel data models with spatial weights matrices that vary over time due to changes in weights has been investigated in the literature starting with Lee and Yu (2012) and Wang and Yu (2015), research on estimation

methods for unbalanced panels – i.e., in the presence of missing data - is less developed (Bouayad-Agha, Le Gallo, and Vedrine 2018). Imputation methods could be used to recover the missing observations, but they may themselves introduce additional sources of bias (Anselin, Le Gallo and Jayet 2008, p.255)

[11] In Italy, NUTS3 units corresponds to 110 provinces. In this analysis, four pairs of adjacent NUTS3 have been merged into four aggregate ones due to their small size of the FADN sample.

[12] Although the balanced micro panel could also be used, as no spatial gap would remain in the aggregate panel anyway, the unbalanced panel seems more suitable to exploit the whole available information. As could be expected, however, aggregating the balanced or the unbalanced panel does not make any significant difference. Online supplementary material with Table S1 provides descriptive statistics of the computed MTFP in the two cases. It is confirmed that, besides some differences in extreme values, MTFP distributions are very similar.

[13] Among the alternative approaches reviewed by Hill (2004), the MST method is preferred here because it is based on the comparison of production structures and because it is suitable for short panels being focused on the cross-sectional dimension of the data.

[14] Therefore, no other unit-specific time-invariant variable, **Z**, is included.

[15] As an economy of scale is the cost advantage of a farm implied by an increased output level, the economic farm size seems a more suitable variable than physical farm size (usually expressed by farm hectares) to capture the returns to scale. This is also the most common way to measure farm size followed by national statistical offices (Khalil et al. 2017). It is the case of the USDA and, more importantly here, of the EU national statistical services managing the FADN. Within the FADN, until 2007 the economic size of the farm was measured as Standard Gross Margin (SGM). Since 2010, the SGM has been replaced by the Standard Output (SO) which is the measure here adopted. It is also worth noticing that this measure of the farm size is more time-variant and less location-specific than the physical size in hectare. In both the micro and the macro panel, this latter variable is almost constant over the time period under analysis and is strongly spatially-dependent. Very large farms are usually found in mountainous areas (mostly extensive livestock farming) while, on the contrary, very small ones in terms of hectares (like intensive livestock farming or horticulture) tend to concentrate in lowland and fertile areas. Physical size would thus return a misleading expression of the actual scale of the farming activity and would actually contain a redundant information on the time-invariant place-specific farming conditions already expressed by other model variables (**Z**).

[16] As discusses in previous sections, these time-variant productivity determinants may be themselves location-specific thus incorporating both production fundamentals and spillovers. Nonetheless, in practice, these three variables show limited spatial correlation, also because the variable expressing the extreme weather conditions is just a dummy capturing extreme temperature. Online supplementary material to the present paper at Table S2 provides descriptive evidence (Moran tests) on this aspect. While in the micro panel spatial correlation weakly emerges, evidence at macro level is mixed. We thank an anonymous reviewer for helpful remarks and suggestions on this aspect.

[17] Elhorst (2012, p. 23) notices that this estimator can also be used when the time and spatial lag of the dependent variable (i.e., $\mathbf{WY}_{t-1}$) is removed from the model, as in the present case.

[18] More details on this method, as well as on its advantages compared to the MCMC approach, can be found in Lindgren and Rue (2015).

[19] Therefore, estimates based on micro data are not commented further. These estimates are reported in Appendix C.

[20] Estimation on alternative **W** and model specifications can be performed with the code provided in the online supplementary material.

[21] Due to space limitations, in Table 3 the estimated coefficients of the time-dummies and production specializations are not reported here. These estimates are provided in the online supplementary material in Table S3.

[22] The actual stability condition of model (8)-(10) depends on the combination of the time and space correlation, therefore by the fact that the sum of the two estimated coefficients is statistically lower than one. This condition is respected in all estimates.

[23] Due to its considerable computational complexity, the MML estimation is not performed here on the micro (farm-level) panel (see Appendix C).

[24] Caserta is more similar to Parma than all the other units in Campania as both regions are specialized in dairy farming.

[25] The long-term indirect effects are often called *diffusion effects* in spatial analysis (Debarsy, Ertur and LeSage 2012). Here, we prefer to maintain the denominations *spill-ins* and *spillovers* as they are more often adopted within the literature on productivity and innovation.

[26] Similar indicators obtained as ratios of different cumulated effects across space are discussed in Elhorst (2012).

[27] It can be easily noticed that for any matrix the average row sum is equal to the average column sum. Therefore, the mean spillovers and the mean spill-ins always correspond and, consequently, the mean absorption capacity always equals 1.