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AGRICULTURAL PRODUCTIVITY IN SPACE

AN ECONOMETRIC ASSESSMENT ON ITALIAN FARM-LEVEL DATA

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Abstract

This work aims to investigate the spatial dependence of agricultural Total Factor Productivity (TFP) by using farm-level data and aggregating them at a variable geographical scale. At this scale a multilateral TFP index is computed and the spatial and time dependence of this TFP measure is assessed within a spatial dynamic panel specification. Alternative Least Squares (LS), Maximum Likelihood (ML) and Generalized Method of Moments (GMM) estimation approaches are proposed and respective results compared. The application concerns Italian farm-level data over the period 2008-2015. Results suggests that higher productivity spillovers are found for those NUTS3 regions with similar neighborhoods in terms of production specialization. Higher spill-ins are found in those NUTS3 with a larger number of geographical connections, regardless of their similarity in terms of production specialization.

Keywords: Productivity Spatial Dependence, Technological Spillovers, Multilateral TFP index, Dynamic Panel Models.
JEL Classification: Q12, O47, C23.

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1. Introduction

In recent years, among agricultural and environmental economists there has been a growing interest in the spatial dimension of agriculture. This can be explained by the increasing and unprecedented availability of large spatially explicit datasets allowing for the investigation of many phenomena at a very small geographical scale. At the same time, however, this interest is also induced by the fact that researchers are increasingly recognizing the value of better understanding the spatial dimension and dependence of agricultural activity and, therefore, how to improve the targeting and design of agricultural policies in this respect. These arguments seem particularly relevant in the specific analysis of agricultural productivity (Wood et al., 2016). On the one hand, spatial differentials of agricultural productivity can be remarkable mostly due to the different farming systems which are, in turn, determined by the specific local environmental, social and economic context. On the other hand, "spatial movement of agricultural technologies has played an important role in the development of agriculture" (Alston and Pardey, 2014, p. 137).

This paper aims at modeling and estimating the spatial dependence of agricultural Total Factor Productivity (TFP) over a flexible geographical scale. Previous empirical works in this field uses highly aggregated spatial data. Here the use of farm-level data allows for a lower level of geographical aggregation compared to most previous studies and, thus, provides evidence on how a too high aggregation level may eventually conceal the actual spatial dependence of agricultural productivity. Therefore, the main objective of this modelling approach is to assess the actual magnitude, direction and spatial scale of the agricultural TFP spatial dependence. More in detail, this empirical analysis is both able to identify agricultural productivity clusters across space and to assess how productivity shocks diffuse over space, thus the spatial scale of technological spillovers. Such an evidence seems particularly helpful in designing policies and, in particular, in better targeting and guiding public R&D investments and in organizing extension services and dissemination activities at the most appropriate institutional and administrative levels.

In order to compare productivity levels across time and space, a Multilateral Total Factor Productivity (MTFP) index is computed on the abovementioned aggregated farm-level output and input data. This MTFP index is achieved through an adaptation of the approach proposed by Hill (1999; 2004), that is, by chaining bilateral comparisons across a minimum spanning tree. Vertexes of this spanning tree are represented by all space-time units while edges are bilateral Fisher comparisons. Productivity dependence across time and, above all, space is then identified and estimated by specifying a dynamic spatial panel model. Estimation is performed with alternative estimators, namely, the Bias-Corrected Least Squares with Dummy Variables estimator (BCLSDV), the mixed Maximum Likelihood/Biased-Corrected Least Squares with Dummy Variables (ML-BCLSDV) and the GMM estimator (Elhorst, 2010b). The contiguity matrix is specified according to a varying radius in order to identify the best-fitting spatial structure. On the basis of the selected model estimates, it is possible to assess how productivity shock occurring in specific locations diffuse over time and space and, thus, to assess the magnitude and range of spatial productivity spillovers. It is also possible to identify the territorial units seizing the highest spill-ins from the surrounding space.

This approach is applied to the balanced panel of Italian FADN (Farm Accountancy Data Network) farms observed over the period 2008-2015. A dense spatial aggregation level is adopted (NUTS3 level), i.e., 106 territorial units (the Italian provinces). It emerges that spatial productivity clusters clearly exist within the Italian agriculture and this explains why the diffusion of productivity shocks (the productivity spillovers) remains confined in a quite limited space. These local spillovers occur quite rapidly as they reach their maximum level after few time periods. At the same time, longer-run spillover effects vary remarkably in space across provinces with some units generating a productivity impact on a national scale over a longer period. The paper finally draws some policy implications of these results in terms of designing research, extension and dissemination policies.

2. Agricultural productivity in space: main issues

2.1. The problem of spatial aggregation

The analysis of agricultural productivity, its dynamics, causes and differentials is very popular in the empirical literature. Starting with the seventies (Ball et al., 1985) a vast production of studies has emphasized the role of a highly growing agricultural productivity in compensating the growing demand of food worldwide still maintaining real prices at low levels and facing increasing natural constraints. In the last decade, the debate on agricultural TFP reignited due to the period of intense agricultural price growth that could signal substantial difficulties the supply side is encountering in keeping the pace of the increasing global demand but also due to a substantial shift observed in recent TFP performance at the level of macroareas (Fuglie, 2008). According to several studies (Alston and Pardey, 2014; Fuglie 2015; Fuglie et al., 2016;), developing countries are now showing an higher dynamics with respect to the developed countries. Such an evidence has been interpreted as a consequence of specific policies. On the one hand, a decreasing public agricultural R&D effort (i.e., real expenditure) in developed countries (Alston and Pardey, 2014); on the other hand, the increasing environmental concerns and natural constraints implied by intensive agriculture that induced supply-containing policies or, more generally, that reduced the policy support coupled to production (Esposti, 2017a, b).

Nonetheless, the empirical evidence on which these policy implications are drawn are highly aggregated studies where TFP is measured (usually in the form of productivity indices) aggregating inputs and outputs over very large geographical areas, i.e., countries or group of countries. In fact, deriving policy conclusions from this kind of evidence may be misleading for two substantial reasons. First of all, aggregation may generate what it is often called an "*ecological fallacy*" (Goldstein, 2003; Wakefield and Lyons, 2010), that is evidence on large aggregation comparisons is used to derive implications at the individual (i.e., farm) level. For instance, two countries can have both two groups of very homogeneous farms: dairy farms and cereal farms. In both countries the former shows a much higher productivity than the latter. However, in one country dairy farms are much more frequent than in the other countries. Consequently, even if in this latter country the average productivity of the two groups of farms is higher than in the former country, it is still going to suffer an aggregate TFP delay. One might argue that, after all, this is the consequence of allocative inefficiency of this lagging behind country but, in fact, freely moving from one production to another can not be easy in this specific case or can be even prevented by its specific natural and environmental constraints. Another example could be that of two countries each with two farms. In one country these two farms show the same TFP level; in the other country, one farm shows a very high productivity level, the other a very low one. Aggregating data would eventually indicate the same country-level TFP but this should be never interpreted as an evidence of a similar technological level of the two agricultures.

The inconsistency of conclusions derived from highly aggregated data when referred to lower level of aggregation or even to individuals is actually manifest in many empirical studies where regressions based on TFP measures are performed under the assumption of independent disturbances. Assumption which is likely to be not appropriate for data aggregated from highly heterogeneous population with grouped structure. This wrong assumption actually leads to a spurious regression due to a misspecification error and, eventually, to downward biased estimated standard errors (Moulton, 1990).

A second reason why agricultural TFP analysis at a very high aggregation may not have consistent policy implications concerns the mechanisms through which TFP and its shocks diffuse across space and across farms. These are economic and sociological mechanisms that are usually dependent on spatial and technological contiguity. Spillovers and imitation as well as congestion effects, that is, localized economies or diseconomies (positive or negative externalities) (Esposti, 2011) eventually generates this *spatial dependence* that can be observed, however, only at an appropriate scale. This scale can not be too large as in this case such proximity effects would be mostly lost or mixed-up. In fact, at a very high level of aggregation most of these mechanisms remain unobserved and, consequently, the relative policy implications are themselves lost or inconclusive. As a matter of fact, the main policy implication derived from the evidence of contiguity effects or spatial dependence at this very high level of aggregation concerns R&D and technological spillovers across countries or groups of countries (Esposti, 2002). But this is just a very rough evidence of mechanisms that in all sectors (Aiello et al., 2014; Cardamone, 2014) and particularly in agriculture (Esposti, 2011; Wood et al., 2016) actually occurs at a very low geographical scale.

The possible inconsistency of conclusions derived from highly aggregate agricultural TFP comparisons justifies the increasing interest on analyses performed on farm-level data (Gray et al., 2011). Farm-based productivity studies, however, may present problematic issues as well. Econometric estimations of farm-level TFP have been carried out on large balanced panels (Bokusheva and Čechura, 2017) but they incur serious limitations when productivity spatial dependence has to be investigated and the underlying mechanisms assessed. These difficulties arise from the fact that the farm level can be too small to investigate such dependence. First of all, for a computational reason as these large panel would imply a very complex and large distance matrix to be included in the analysis and eventually estimated. In practice, the identification and estimation of such spatial structure can be empirically unfeasible unless some assumptions are made in this respect (Cardamone, 2014; Baltagi et al., 2016). Beside this dimensionality issue, however, the farm-level scale may be too small because spatial contiguity among farms does not properly capture the scale at which technological and productivity interdependence occurs. The proper scale is an intermediate: some local/regional scale instead of a country or macro-regional scale or a micro scale.

In practice, some level of geographical aggregation of farm data is needed. This level may be different according to the specific context and the farm typology itself. So, it seems appropriate to put forward an approach that, starting from farm-level data, can aggregate them to compute TFP measures in a very flexible way, that is at different geographical scales and according to different forms of aggregation (including farm size and production specialization). One possible way to tackle this methodological challenge consists in a two-step approach where firm-level TFP is firstly estimated necessarily assuming some underlying production technology within the observed farm panel (Aiello et al., 2014; Bokusheva and Čechura, 2017). Then, some second-level aggregation (i.e., regional) is introduced within the econometric analysis of firm-level TFP in the form of specific random or fixed effects. Alternatively, farm-level data are aggregated at some small geographical scale to compute multilateral TFP indices (therefore, without any econometric estimation) at this level and then spatial dependence of TFP is investigated at this aggregation level. This latter approach seems more flexible in aggregation especially because the second-level (the farm level being the first) does not bring about parameters to be estimated that would imply a curse of dimensionality any time the second-level remains an highly disaggregated one (Gray et al., 2011). Beside allowing for flexible aggregation, this approach based on multilateral TFP indices of farm-level data aggregated at a low scale of geographical aggregation then followed by an econometric investigation of TFP determinants allows in this second stage to include both spatial and time dependency in alternative ways. For this reason, this kind of original approach is proposed and adopted here.

2.2. Agricultural TFP spatial dependence: technological spillovers and more

In order to better understand the proper areal scale of productivity dependence it is necessary to review the underlying economic forces. An extensive overview of the theoretical and empirical literature is well beyond the scope of this paper also because it embraces the whole range of economic activities and does not only concern agriculture. Nonetheless, a discussion on some of the specificities of the agricultural sector can be found in Esposti (2011) and Wood et al. (2016). In general terms, it can be stated that spatial productivity dependence is the eventual outcome of external effects (externalities) generated by any single i-th production unit (firm) and depending on the i-th farm productivity performance. These externalities may be more or less localized and can be either positive or negative though, in fact, most of the literature tends to emphasize the former (as productivity spillovers) on the latter (a productivity drawback).

The main economic force generating a positive externality, thus inducing productivity spillovers, is the diffusion of technology and knowledge and the consequent adoption and adaptation of innovations. This diffusion process may occur over the geographical space and across sectors, especially for highly general (general-purpose or key-enabling) technologies and knowledge. But for the largest part the diffusion occurs within an industry and, especially when this industry shows a strong a site-specificity, it tends to be localised, thus limited in space (Esposti, 2011). Technology and knowledge diffusion may eventually produce a second-order (or indirect) positive external effect. Especially in sectors highly exposed to competition, more productive farms induce competing production units to absorb and apply new knowledge in order to retain market shares. The more this market competition is played at the local level the more this external effect will be spatially confined (Gray et al., 2011).

Besides this largely known and investigated spillover mechanisms that eventually imply a positive TFP spatial dependence, however, other forces may counteract by generating a negative TFP spatial dependence. These external diseconomies are mostly due to competition among firms, sectors and territories. On the first aspect, it is worth noticing that firms achieving higher productivity force a reallocation of production inputs from less productive ones. This reallocation tends to be selective, that is, it mostly concerns inputs and resources of better quality. Consequently, this reallocation may imply a negative externality of highly productive farm on less productive ones, i.e., a productivity drawback. This negative effect is more localised the more local is the competition for production inputs both in terms of quantity and quality. This negative effect of competition can also occur for public expenditure or resources, especially those dedicated to R&D, innovation, technology and knowledge diffusion. More productive firms and, above, all sectors and territories may attract and capture more resources thus subtracting them from less productive contexts. These indirectly generate a productivity drawback that tends to be local, thus taking the form of negative spatial dependence, the more the allocation of public resources is based on a local institutional setting. In other words, the more the public budget constraint is localised the higher the local competition for these resources (Esposti, 2011).

Paying specific attention to agriculture, it can be generally concluded that all these forces are particularly active and tend to be more localised compared to other sectors. This peculiarity depends on the fact that farming is a strongly site-specific activity, it is typically exposed to both local and global competition on output markets but some key inputs (labor and, more peculiarly, land) are local and move only on a small geographical scale (in fact, land mobility is null by definition), thus competition for inputs is strongly local. Consequently, in agriculture we may expect that both positive and negative TFP spatial dependence is magnified. In particular, the main peculiarity of agriculture is that the farming activity is highly heterogeneous across space due to unchangeable and nontransferable environmental (both ecological or social-historical) factors and the consequent factor endowments (Esposti, 2011). For this, the sector tends to be organized in localised farming systems (Wood et al., 2016). As a consequence, technology itself is spatially specific because it is often designed specifically, or more tailored, on specific farming systems (for instance, production specialization) (Esposti, 2011). This is not, in fact, exclusive of agriculture. Acemoglu and Zilibotti (2001) have argued that aggregate productivity differentials can be explained by the fact that innovations are developed in specific economic environments, with specific factor availability and prices. When those conditions are not perfectly met, technology diffusion could not achieve its full potential in terms of productivity gains.

The empirical literature on agricultural technological spillovers emphasizes these two conflicting aspects. On the one hand, agricultural innovations are largely and often freely transmitted in the form of inter-sectoral and inter-regional spillovers (Alfranca and Huffman, 2003; Huffman and Evenson, 2001; Esposti, 2002). At the same time, empirical evidence still points to large cross-country productivity differentials (Acquaye et al., 2002; Sheng et al., 2014). Large differentials are also found across regions within the same country (Hayami and Ruttan, 1970; Maietta and Viganò, 1995; Pierani, 2009). To reconcile these two facts, it is usually concluded that these productivity differentials depend on differential diffusion processes of innovations due the typical local specificity of farming (Griliches, 1960; Hayami and Ruttan, 1970).

Therefore, forces inducing TFP spatial dependence in agriculture are those factors that influence the site-specific nature of agricultural technology. Moreover, (localized) farming systems tend to facilitate the process of technological diffusion and adoption (localized positive externalities or economies) and to induce the improvement of the quality of inputs, the provision of public goods, the functioning of the local markets of both inputs and outputs but also, inevitably, the degree of local market competition. At the end, all the forces eventually affecting the spatial dependence are strongly reinforced within localised farming systems, also including that some of the environmental factors eventually inducing this system organization may themselves affect the productive performance.[1]

3. Data, aggregation levels and productivity indices

The empirical analysis of spatial TFP dependence is here performed on the farm-level data provided by the Italian FADN sample over the years 2008-2015. The sample consists of an unbalanced panel of about 11,000 commercial farms annually sampled with a stratified random sampling strategy to be statistically representative across farm production specializations and across geographical units. A weight can be further associated to each sampled farm in order to make the extracted sample representative also for territorial levels other than that used for sample extraction.[2]

Weighted prices and quantities observed at this farm level are then aggregated to build aggregate input, output and, then, TFP indices. As the elementary data are observed at the farm-level, aggregation can be performed in many different ways, such flexibility allows not only the comparison of productivity performance across space but also across farm typologies in terms of size, production specialization, etc. (Baldoni et al., 2017). As spatial dependence is of main interest here, the aggregation considered concerns the 106 Italian NUTS3 units.[3] Therefore, the TFP is computed and its spatial dependence assessed on this balanced panel of 106 units observed over 8 years (2008-2015).

In the present analysis, productivity measurements and comparisons across this spatial panel is achieved by computing a multilateral (transitive) TFP index following the Hick-Moorsteen approach (Coelli et al., 2005; Fried et al., 2008). As well known, index numbers are not the only available methodology for productivity measurement and comparison at either some aggregate level or the farm level. Alternative

[1] For instance, a largely emphasized driver of agricultural productivity in recent years is climate change whose effects are evidently site-specific (Wood et al., 2016).
[2] This weighing procedure is also adopted here. More details on the Italian FADN sample, its extraction and representativeness can be found in Cagliero et al. (2011). The period of analysis is limited to years 2008-2015 due to the change occurred in the sampling protocol that would make the comparison with previous years difficult and would strongly reduce the size of the sample. Moreover, as emphasized by Esposti (2017a,b), the farm performance in Italy during years 2005-2007 has been strongly affected by the major change of the CAP support and of the consequent farms' choices.
[3] The number of NUTS3 according to Eurostat classification corresponds to the administrative division of Italian provinces as of 2011. In the present research, four provinces were merged together with neighboring ones in order to derive detailed accounts of inputs and outputs for every spatial unit.

widely used techniques to estimate productivity performances are the Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) (Coelli et al., 2005; Fried et al., 2008). These are based respectively on the parametric and non-parametric estimation of the production frontiers and on the measurement of the deviation of any unit from this frontier. However, the index number methodology is here preferred as it allows for the derivation of a single productivity index that can be used to compare performances across units and over time in a relatively simple and flexible way despite the very large number of inputs and outputs observed at the farm level (see below). Moreover, productivity indices do not require specific assumptions regarding functional forms and do not involve often complex estimation procedures.

Nonetheless, the application of the index number approach to productivity measurement within a panel dataset raises serious complications. The HM index is constructed as a ratio of a Fisher output quantity index to a Fisher input quantity index. Under the assumption that the distance functions underlying the outputs and inputs aggregations are quadratic functions with identical second order parameters, the Fisher index approximates the theoretical Malmquist index, i.e., it is a superlative indices as it is exact for the quadratic, thus, flexible, production function (Coelli et al., 2005). Moreover, among all index numbers, the Fisher index satisfies most the desirable statistical properties (Fisher, 1922) and it is grounded on economic theory as it provides meaningful aggregation method for outputs and inputs without imposing assumptions on the shape of the underlying production technology (Van Biesebroeck, 2007).

However, when applied to a panel dataset, thus whenever productivity comparisons are performed over time and across units at once, the Fisher index (as well as all other index numbers, the Malmquist index included) does not satisfy the transitivity property. Following Hill (2004), this property can be formulated as follows:

(1) $$QI_{it,js} = QI_{it,kq} \cdot QI_{kq,js}$$

where i, j and k indicates three generic units while t, s and q three generic time periods. Therefore, (1) can be described as the equality of a bilateral comparison between unit j in period s and unit k in periods t with an indirect comparison via unit m in time period u.[4] Transitivity is a very important property for productivity comparisons within a panel, as it implies that the rank of the productivity performance is independent of the unit and the time chosen as basis for the construction of the index. For this reason, indices satisfying this transitivity property are also called transitive or multilateral productivity indices.

The literature has proposed two main alternative solutions to obtain multilateral (transitive) productivity indices. The first method is based on the idea that aggregate output and input indices can be derived by comparing all units under analysis simultaneously. This is the EKS (Eltető -Köves-Szulc) approach (Rao et al., 2002). The main issue with this methodology is that it considers all binary comparisons as equally reliable. However, in many contexts (and agriculture definitely is one of these), it is well known that some comparisons are more reliable than others as this reliability stems from the similarity of the observations (i.e., units and periods) that are compared. Because of the failure of the EKS transitivity procedure in recognizing this aspect, output and input aggregate indices can be obtained taking into account that comparisons across a set of units over time can be made by chaining together bilateral comparisons that are selected based on the similarities among units. This method is called *Minimum Spanning Tree* (MST) approach and requires the selection of a set of bilateral comparisons to be chained together in a spanning tree.[5] The set of bilateral comparisons is established through a specific procedure

[4] In practice, bilateral index between units A and B is transitive if it is equal to the product of the bilateral comparisons of A and B through a third unit C.

[5] Hill (2004) overviews and compares six available methodologies to derive transitive measurements in a panel data context,. They are: the minimum-temporally-fixed-graph, the temporally-consistent graph, the spatially-consistent graph, the temporally-fixed-grid graph, the multilateral approach and the minimum spanning tree. No consensus has emerged over which methodology is best to derive panel robust indices. In the present research, the minimum spanning tree method has been

that identifies the best pairs of producing units based on the similarities of their prices and quantities. Therefore, for any generic j-th unit (region) and t-th time (year) the aggregate input and output indices are transitive indices obtained by chaining, across a spanning tree, all the space-time observations of the panel using bilateral Fisher comparisons. The spanning tree is identified as the one that minimizes the global distance between the nodes of the tree where the distances are defined as the Paasche-Laspeyres Spreads (PLS), i.e., minimizes the sum of the Paasche-Laspeyres spreads between each bilateral comparison (Hill, 1999; 2004). Following this methodology, aggregate output and input transitive indices are computed for any unit and any period of time. Eventually, the multilateral HM TFP index is derived as a ratio of these two transitive aggregate indices.

Fisher output and input indices for any of the 106 units and 8 years (848 observations) are obtained by aggregating the respective farm-level data available in the FADN dataset. Production information therein is very rich. On the input side, the following factors have been considered: labor, capital, land, fertilizers, pesticides, external services, water, electricity, seeds, feeding stuff, reuses and other general expenses. On the output side, the dataset provides a very detailed and rich list of farm productions (services included). From a large set of 1080 products, 346 more general categories have been created before proceeding with the index number aggregation.

3.1. The Italian agricultural TFP across space

Figure 1 reports the multilateral output and input indices averaged over the 2008-2015 period at the adopted geographic scale of analysis (NUTS3), while Figure 2 reports the consequent average multilateral TFP index and its average annual growth rate in the period. Some aspects are worth noticing. First of all, a remarkable heterogeneity emerges in both productivity levels and growth. Secondly, some spatial patterns can be identified as clusters of regions with similar performance but these clusters do not necessarily correspond when considering TFP levels and growth. At the same time, the scale of the clustering, thus spatial dependence, seems to be lower compared to the usual geographical aggregates on which the Italian differential, and sometime dual, development is interpreted. In fact, no clear North-South or East-West gradient can be detected (Esposti, 2012, 2014). If some geographical pattern had to be identified, it would rather emerge that higher productivity levels and growth rates tend to concentrate in some North-eastern provinces (Pianura Padana) and in some Southern provinces (especially in Calabria and Sicily).

This simple visual inspection thus reveals that productivity spatial heterogeneity and dependence may occur in Italian agriculture but deriving conclusions and implications is much more complex than usually considered. Nonetheless, the adopted scale of analysis seems dense and rich enough to investigate this dependence without incurring in severe computational problems due to dimensionality of the spatial dimension. On the one hand, these results provide a much more vivid and higher-resolution picture of agricultural productivity differentials in Italy compared to previous literature. Among others, interesting references in this respect are Maietta and Viganò (1995), Rizzi and Pierani (2006), Pierani (2009) and Esposti (2011). On the other hand, and more importantly, the adopted approach based on farm-level data aggregation turns out to be more flexible than previous works in terms of aggregation adopted.

To better stress this aspect, Table 1 compares the agricultural productivity performance (average TFP level and growth rates) across different either spatial or non-spatial aggregations: macroregions; altitude

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preferred over the others for the following reasons: i) it is based on the idea of comparing production units with a similar production structure; ii) the period of analysis is narrow and the MST method focuses especially on the cross-sectional nature of the data; iii) it is easier to implement with respect to other methodologies; iv) it is not sensitive to the reference space-time units chosen.

classes, farm sizes and production specializations.[6] This descriptive evidence confirms the two main stylized facts worth noticing here: productivity differentials within Italian agriculture are large; no aggregation is actually able to fully represent such heterogeneity. Spatial differentials are much more evident across altitude classes than on a North-South gradient. Moreover, these differentials may be, in fact, generated by the different composition in terms of size classes and production specializations across space. Aggregating across size and specializations eventually reveals even more marked differentials in favor of larger-sized farms and of both capital (dairy) and labor (fruits) intensive specializations.

3.2. Testing for productivity spatial dependence

To more explicitly assess the presence of productivity spatial dependence among Italian NUTS3 units, a Moran I test is performed (LeSage and Pace, 2009). This is a test for the statistical significance of a linear association between the TFP measure in a given NUTS3 unit and the average TFP of its neighbors. To perform such test, an assumption regarding the spatial link structure needs to be done. Two typical solutions are: i) consider as neighbors only bordering units; ii) consider as neighbors all those units whose centroid falls within a pre-defined radial distance. This radial distance is generally arbitrarily defined. Here, to avoid strong assumptions about this spatial structure, a series of tests with alternative assumptions combining both approaches have been carried out and the results presented in Figure 3. The Moran statistics is computed by iteratively augmenting the queen adjacency structure with those NUTS3 units whose centroid falls within an increasing radial distance (horizontal axis). The Moran statistics (left vertical axis) and the respective significance level (p-value; right vertical axis) are computed on the logarithm of the average TFP level over the whole period.

Test results suggest that positive spatial correlation of TFP occurs, thus indicating productivity clustering. However, this correlation seems to be limited in magnitude and space. The coefficient of spatial correlation varies between 0 and 0.22. The highest value is found considering radial distances between 20 and 60 kilometers. By further increasing this distance, the magnitude of spatial correlation decreases and becomes almost negligible for radius lengths larger than 300 kilometers. A positive but small correlation exists also for radial lengths between 60 and 300 kilometers but appears to be smaller with a peak in magnitude at around 150 kilometers. This suggests a relatively narrow spatial correlation structure of TFP between NUTS3. A major implication of this result is that any analysis of TFP dependence across space using a coarser spatial structure (NUTS 2 regions, macroregions or, even more, the country level) may substantially fail in detecting the actual degree of this dependence and, above all, its underlying mechanisms.

4. Modelling productivity dependence within the panel

In order to model agricultural TFP dependence within a panel dataset two different forms of correlation have to be taken into account when looking for the proper specification and, consequently, estimation approach. The first correlation may occur over the time dimension. The presence of autocorrelation in TFP series has been pointed out in several studies based on aggregate data (Slade, 1988; Basu, 1996). The main argument motivating this behavior is that productivity measures tend to be procyclical as they capture all those short-term output variations not captured by observable variations in input consumption (for instance, higher capacity utilization). In the agricultural sector such time dependency of TFP measurement is considered even more relevant due to further forces and events that can link the unexplained output growth across years or time periods (meteorological conditions, pests, ecc.) (Esposti, 2000; 2011). In practice, this means to model TFP within a panel admitting a time

[6] For this latter, only relevant cases are reported. The whole set of results is available upon request.

autocorrelation term. As we are working with annual TFP measures and given that the temporal dimension of the dataset is relatively short (8 years) an AR(1) term is here considered.

The second form of correlation is what interests more here. It expresses productivity spatial dependence and, therefore, productivity clustering as well as the diffusion process of productivity shocks across space. Like correlation over the time dimension, spatial correlation may be modelled introducing lagged spatial variables. Unlike time, however, spatial lags are not unidimensional and require the specification of a *N*x*N* distance or spatial weight matrix $\mathbf{W}$ identifying whether and to what extent the productivity of any of the *N* regions affects the productivity of all the others.[7]

It follows that the easiest specification admitting both temporal and spatial dependence is the following dynamic spatial linear relation:

$$\text{(2a)} \qquad \mathbf{TFP}_t = \rho\, \mathbf{TFP}_{t-1} + \delta \mathbf{W}\, \mathbf{TFP}_t + \mathbf{X}_t\, \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t, \quad \forall t \in \mathrm{T}, \quad \mathrm{T} = 2008,\ldots,2015$$

Where $\mathbf{TFP}_t$ is the *N*x1 vector of productivity levels at time t, $\mathbf{X}_t$ is a *N*x*M* matrix of *M* exogenous variables affecting productivity performance beside time and spatial dependence. ρ and δ are the two unknown autoregressive coefficients while $\boldsymbol{\beta}$ is the *M*x1 vector of the unknown coefficients associated with the exogenous variables contained in $\mathbf{X}$. $\boldsymbol{\varepsilon}_t$ is the *N*x1 vector of the usual disturbance terms assumed to be identically and normally distributed with mean zero and variance σ^2 . The normality assumption on the disturbance term implies that the dependent variable itself is assumed to be normally distributed. This assumption, however, is clearly violated due to the strong asymmetry of the *TFP* within the sample as it ranges in the [0,∞) interval (cases with zero TFP are evidently lacking). For this same reason, however, its log-normal distribution over the [0,∞) support can be largely accepted. Therefore, in (2a) the TFP enters as logarithmic transformation rather than as level.

If, as in the present case, the vector of exogenous variables, **X**, also includes a constant term and regional dummies we obtain a fixed-effect panel specification. Consequently, (2a) is a dynamic space-time panel model (Debarsy et al., 2012) and, in particular, a *Spatial AutoRegressive* (SAR) *model*. It can be considered as a special case of the more general specification known as the *Manski model* where spatial dependence is also admitted for the exogenous variables and the error term or of its feasible (i.e., estimable) specification known as the *Spatial Durbin Model* (SDM) that admits both the exogenous and the endogenous interaction effects (LeSage and Pace, 2009; Elhorst, 2010a; Camaioni et al., 2016). The SAR specification is here adopted because the exogenous variables considered in the present analysis (see below) express structural features of the regions for which no diffusion process can be conjectured. In fact, in the present analysis spatial dependence only comes from endogenous interaction effects.

Despite this simplification, (2a) still implies autocorrelation of the disturbances and non-linearity in the parameters. Therefore, the consistent estimation of (2a) can not be performed through OLS (see next section). This occurs because the endogeneity in (2a) implies that the reduced estimable form has to be written as follows:

$$\text{(2b)} \qquad \mathbf{TFP}_t = \left[(\mathbf{I} - \delta\mathbf{W})(\text{-}\ \rho L)\right]^{-1} \mathbf{X}_t \boldsymbol{\beta} + \left[(\mathbf{I} - \delta\mathbf{W})(\text{-}\ \rho L)\right]^{-1} \boldsymbol{\varepsilon}_t$$

(2b) also suggests that spatial dependence in (2a) is not only expressed by the parameter δ (the *pure spatial effect*) but also by the complex feedbacks due to $\mathbf{W}$ and ρ. This space-time dependence structure seems particularly helpful to make the productivity dependence explicit in terms of diffusion of productivity shocks. Following (2b), an unitary agricultural productivity shock on the i-th unit affects the i-th productivity performance in the following years and also generates a productivity spillover to

[7] The advent of spatial econometric models strongly fostered the empirical investigation on diffusion processes. Recent examples of this empirical literature not concerning productivity spillovers are Parent and LeSage (2010) and Debarsy et al. (2012). Concerning productivity and the respective diffusion processes, see Aiello et al. (2014).

other NUTS3 depending on δ and $\mathbf{W}$ but also on ρ. This occurs because this spillover effect is initially due to the simultaneous effect implied by the spatial dependence but then it persists over time, though declining under stationarity (i.e., if $|\rho| < 1$), because of time dependence. Therefore, the overall effect of a random unitary productivity shock occurring at time *t* in the generic i-th region is the combination of two cumulative impacts: on the space dimension, the summation of the simultaneous response of all regions, $\sum_{j=1}^{N} \frac{\partial TFP_{jt}}{\partial \varepsilon_{it}}, \forall j \neq i \in N, \forall t \in T$; on the time dimension, the cumulation of the impact on a generic j-th region over time, $\sum_{s=1}^{T-s} \frac{\partial TFP_{jt+s}}{\partial \varepsilon_{it}}, \forall j \neq i \in N, \forall t \in T$.

This complex diffusion effect can be more explicitly expressed through a *diffusion matrix*. This matrix contains all the information on the space-time dependence of TFP to quantify the effect of a random unitary productivity shock occurring in a specific region. It can be derived directly from (2b) by stacking vectors and matrices over the time dimension:

(2c) $$\mathbf{TFP} = \mathbf{D}^{-1}\mathbf{X}\boldsymbol{\beta} + \mathbf{D}^{-1}\boldsymbol{\varepsilon}$$

where $\mathbf{TFP} = \left(\mathbf{TFP}_1',..., \mathbf{TFP}_T'\right)'$ is an *NT*x1 vector, $\mathbf{X} = \left(\mathbf{X}_1',..., \mathbf{X}_T'\right)'$ an *NT*x*K* matrix and $\boldsymbol{\varepsilon} = \left(\boldsymbol{\varepsilon}_1',..., \boldsymbol{\varepsilon}_T'\right)'$ an *NT*x1 vector. $\mathbf{D}^{-1}$ is the *NT*x*NT* diffusion matrix corresponding to the inverse of the following:

(3) $$\mathbf{D} = \begin{bmatrix} \mathbf{B} & \mathbf{0} & \cdots & \cdots & \mathbf{0} \\ \mathbf{C} & \mathbf{B} & \cdots & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{C} & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \mathbf{0} & \cdots & \cdots & \mathbf{C} & \mathbf{B} \end{bmatrix}$$

where $\mathbf{B} = (\mathbf{I}_N - \delta \mathbf{W})$ and $\mathbf{C} = -\rho \mathbf{I}_N$.

Using this diffusion matrix three spatial effects of productivity shocks can be identified and estimated for any i-th region:

1. *Productivity spillovers*: the total impact on TFP levels of a unitary productivity shock in the i-th region cumulated over all the other regions and time-period of length T: $S_i^O = \sum_{j=1}^{N} \sum_{t=1}^{T} \frac{\partial TFP_{jt}}{\partial \varepsilon_{1i}}, \forall j \neq i \in N$
2. *Productivity spill-ins*: the total impact on TFP level of the i-th region of unitary productivity shocks in all other regions cumulated over a time-period of length T: $S_i^I = \sum_{j=1}^{N} \sum_{t=1}^{T} \frac{\partial TFP_{it}}{\partial \varepsilon_{1j}}, \forall j \neq i \in N$.
3. *Absorption capacity*: the ratio between productivity spillovers and spill-ins for the i-th region: $AC_i = \frac{S_i^I}{S_i^O}$.

On the basis of these effects, the N regions can then be ranked in order to identify, on the national scale, areas mostly generating and areas mostly capturing productivity improvements. All these effects depend on the two unknown parameters to be estimated δ and ρ as well as on the unknown terms of $\mathbf{W}$. As will be explained below, these are limited to the radial distances defining the neighbouring space. Though it must be established *ex ante* in order to predetermine the spatial structure, the adopted estimation procedure can itself lead to the identification of the most appropriate (i.e., best fitting) radius thus to the most appropriate distance matrix. Therefore, the identification of these spatial effects is entirely determined through the adopted estimation procedure.

Specification (2a)-(2c) and, above all, the consequent computable effects of unitary productivity shocks, seem particularly suitable to investigate agricultural productivity across space.[8] Not only it is able to assess the spatial scale of these effects, i.e., to what extent they tend to remain local. In addition, although contemporaneous effects cannot be not ruled out, 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, the modelling approach is also able to assess the speed at which agricultural technology and innovations spread across space.

5. Estimation

5.1 Alternative estimators

The estimation of model (2a) raises two major concerns. The first deals with the endogeneity inherent in any dynamic space-time panel model. Such endogeneity comes from two different terms, i.e., the time-lagged and the space-lagged dependent variables. While the estimation implications of the former term has been widely investigated in panel data econometrics (Arellano, 2003), the discussion and viable solutions about the latter is more recent. In practice, as anticipated and as clear in (3b), the presence of endogenous terms eventually determines autocorrelation of the disturbances and non-linearity in the parameters. Therefore, the estimation of (2a) can not be performed through OLS as the respective estimates are not consistent.

As well surveyed by Elhorst (2010b), three alternative estimators have been proposed and can be alternatively adopted. The first estimation approach, is an extension of the well-known Bias Corrected LSDV (BCLSDV) estimator to the space-time panel model specification (Yu et al., 2008). Under a stationary dependent variable, this estimator has good asymptotic properties as it is consistent for $N \rightarrow \infty$ and $T \rightarrow \infty$ but also for $N/T \rightarrow \infty$. However, its small sample performance, especially for T small, remains questionable. Alternatively, model (2a) can be consistently estimated via the MLE approach proposed by Hsiao et al. (2002) or by extending to the space-time panel specification the usual Arellano-Bond GMM estimation approach and its extensions (Arellano, 2003). Both ML and GMM estimation can be computationally demanding and, beside their desirable asymptotic properties, their small sample performance can be unsatisfactory as well.

To take advantage of the availability of these different estimators and their different properties, Elhorst (2010b) proposes two mixed estimators. The first obtains an estimation of parameter δ with BCLSDV; then the constrained model is estimated via MLE. This estimation approach is called ML-BCLSDV estimation. In the second mixed approach, the estimated δ parameter with BCLSDV enters a GMM estimation of the whole model. This estimation approach is called GMM-BCLSDV estimation. The Monte Carlo simulations performed by Elhorst (2010b) suggest that the ML-BCLSDV estimator outperforms the others when T is small and the dependent variable is stationary. On the contrary, with

[8] An analogous modelling and estimation approach to investigate productivity spillovers, though not specifically concerning agriculture, has been adopted by Lin and Kwan (2013).

T small but under non-stationarity the GMM estimation should be preferred.[9] For this reason, and for the sake of comparison, model (2a) is here estimated using BCLSDV, GMM and ML-BCLSDV estimators.

5.2 The specification of the spatial weight matrix

The second relevant issue to be dealt with in properly estimating (2a) concerns the specification the NxN spatial matrix **W**. In principle, this matrix is made of NxN unknown elements to be estimated. In practice, this estimation is clearly unfeasible. Even if we reduce the dimension of the problem to few (possibly just one) unknown parameters, they can never be identified separately from parameter δ. Nonetheless, the estimation procedure can be iterated across alternative specifications of **W** in order to find the best fitting one. Following the same approach used to compute the Moran statistics, matrix **W** is here specified as a Queen's adjacency structure iteratively augmented with the NUTS3 units whose centroid falls within an increasing radial length. At each iteration, the i-th row/j-th column element is fixed at 1 if either the j-th region borders the i-th unit or its centroid falls within the pre-determined radial distance from the centroid of the i-th region; at 0 otherwise.

Proximity among regions is not only a matter of space but also of production technology and, therefore, specialization. To take this aspect into account, unlike the Moran test, the **W** matrix here used combines both spatial and technological proximity. To achieve this, any element of the spatial matrix is weighted. Each weight represents the dissimilarity in agricultural specialization between those two NUTS3 regions. In practice, the assumption is that the TFP linkage between any pair of NUTS3 units is stronger the closer is their agricultural specialization. Accordingly, each element w_{ij} of the spatial matrix **W** is weighted (i.e., multiplied) by the technological proximity index (tp_{ij}) measured as the inverse of the distance between region i and region j in terms of their UAA (Utilized agricultural area) shares of the various agricultural productions (i.e., types of farming):

(4) $$tp_{ij} = \frac{1}{d_{ij}}$$

where d_{ij} is the Euclidean distance between the vectors of the regional UAA shares by type of farming.

This weighted spatial matrix is row-standardized before estimation. Starting from the minimum cut-off value of 20 km, the estimation procedure is iterated by increasing this radial distance by 10 Km per iteration up to 300 Km and the value of the respective maximum likelihood function is computed. The best fitting matrix is the one showing the highest value of the maximized log-likelihood function.

5.3 The exogenous variables

Estimated model (3a) is completed by the vector of exogenous variables **X**. Here **X** includes a constant term, the region-specific (dummies) and two further exogenous effects accounting for the geographical dependence of agricultural productivity not accounted for by the other variables. They are average the average altitude[10] of the i-th region and the occurrence of extreme weather events in the i-th region at

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[9] Stationarity in a space-time model is achieved when the sum of the absolute value of the two autocorrelation terms is smaller than one: $|\delta| + |\rho| < 1$. Following Elhorst (2010b), the condition is satisfied when the characteristics roots of the matrix $\rho(\mathbf{I}_N - \delta\mathbf{W})$ are included in the interval $(-1,1)$. This condition is always met in the present case. Conventional panel unit root tests have been also performed on the computed TFP and results clearly indicate stationarity around a deterministic trend. Test results are available upon request. Also, estimations on simulated data under the assumption of non-stationarity have been carried out by the authors and are available upon request.

[10] Average altitude is a time-varying variable as it is computed as the average altitude of the plots belonging to the sampled farms. As the sample changes over the years, average altitude also changes.

time t. This latter one is a dummy variable taking value 1 whenever the annual precipitation is the 36% higher than the regional long-term average.

6. Results

6.1 Model estimates

Figure 4 shows how the value of the maximized log-likelihood[11] varies with the radial distance used to define **W**. The maximized log-likelihood is higher with a radius of 70, 130 and 240 kilometers and these values are associated with a positive and higher value of the coefficient δ. However, the highest maximized likelihood function is found with a radius length of 130 kilometers. Therefore, such distance is here adopted to define matrix **W** entering the estimation of model (2a). Model estimates obtained with the three abovementioned estimators are reported in Table 2.[12]

Results suggest that the three estimators tend to largely agree on the sign and magnitude of model parameters. Nonetheless, their performance in terms of statistical quality expressed by the statistical significance of estimated parameters remarkably differ. While GMM estimation performs poorly in this respect due to much higher estimated standard errors, the best case is the BCLSDV estimation. Both time and spatial dependence is observed and in both cases with a positive sign suggesting, on the one hand, the presence of spatial productivity clusters and, on the other hand, some persistence of productivity shocks over time. Here, the magnitude of the spatial dependence is much higher than the estimated time dependence. Eventually, the spatial dependence turns out to be the main determinant of the regional agricultural productivity performance as the other two variables are hardly statistically significant and, in any case, of much lower magnitude. Both coefficients move in the expected direction as both the occurrence of extreme events and altitude tend to reduce the observed agricultural productivity. Nonetheless, the former is never statistically significant while the latter is significant only under the BCLSDV estimation.

6.2 Spillovers and spill-ins

To analyze the diffusion of productivity shocks across space, thus the presence and the nature of productivity clusters, the best estimates of (2a), i.e., that obtained with the BCLSDV estimator with a radial distance of 130 kilometers to define **W**, is here used. According to equation (2c) and assuming a unitary productivity shock in a given NUTS3 region and year, it is possible to observe how this shock diffuses over time and across space. Several exercises can be carried out in this respect and are presented below in order to better understand how the shock spreads across the neighboring space over time.

Figure 5 shows the results of this exercise with a unit positive productivity shock occurring in the Parma province (in black) at time t. This is one of the most productive and dynamic NUTS3 regions in Italian agriculture which is in turn located in the middle of the most productive area of Italy, i.e., the Pianura Padana (see Figure 2). Depending on **W**, thus on both spatial and technological contiguity, this shock diffuses over the neighboring space and, then, the shock being on the endogenous variable, also towards the non-bordering regions. Evidently, this further effect takes more time to occur. Figure 5 clearly show how the regions that receive the contemporaneous largest shocks due to the original shock in Parma are the neighboring provinces of Reggio Emilia and Modena but also the non-bordering province of Bergamo. Due to the definition of matrix **W**, there is not a mechanical relationship between geographical distance and contagion effects. Reggio Emilia receives a larger shock both because it is geographically close to Parma but also, and most importantly, because it shares a more similar

[11] The likelihood is concentrated around δ.

[12] All model estimates and all testing procedures are performed using the R software (R Core Team, 2013), and in particular the package 'spdep' (Bivand et al., 2013; Bivand and Piras, 2015). Following Elhorst (2010b), the codes of the BCLSDV and the ML-BCLSDV estimators have been developed by the authors.

production structure with respect to Piacenza. Parma, Reggio Emilia and Modena are all similarly specialized in both dairy and arable crops. The similarity in their production structure facilitates the spread of TFP across these NUTS3 units. The large effect occurring in Bergamo depends on its specialization much more than on spatial contiguity.

The adopted specification of matrix **W** thus allows for a complex spatial interaction between regions. Figure 5 also shows that, as implied by stationarity, at time $t + 1$ the effect of the shock decreases considerably. More generally, over time the effect of the shock fades to zero quite rapidly. Thus, the spatial diffusion process depends on two aspects. On the one hand, the effect of a shock rapidly vanishes over time due to stationarity and to the small value of the autoregressive coefficient. In practice, in three time periods the effect of the original shock seems to be vanished. On the other hand, however, the endogeneity of the shocked variable makes the shock occurring on unit i-th indirectly affect also the relatively faraway regions. In fact, it is worth noticing that, due to the complexity of the diffusion process, an impact can be observed also on regions that are significantly further away from the origin of the shock.

Figure 6 shows how the shock in Parma diffuses in NUTS3 units in Campania, around 600 kilometers away. The first thing to be noted is that the effect of the shock is remarkably smaller than the effect occurring in the proximity of the source of the shock. However, the temporal profile of the contagion remains the same even at relatively large distances. The contemporaneous shock is the largest in the first time period for all NUTS3 units and fades to zero over time. Spillovers curves, presented in Figure 6, are obtained by cumulating over the whole period the effects of the shock occurred at time t in every NUTS3 considered. This exercise is particularly interesting to understand the drivers of this diffusion process. In fact, in this case geographical distance plays a small role in determining the difference in magnitude of the effects as all NUTS3 in Campania are at similar distances from Parma. Despite this, magnitude of the shocks here are remarkably different, with Caserta receiving a much larger effect than all the other NUTS3 units. Also Benevento and Napoli receive a positive shock while Avellino receives a much smaller effect than the other three units.

These differences in spillovers received can be explained by their similarity in term of production structure with Parma. Caserta is much more similar to Parma than all the other units with both regions specialized in dairy farming. Also Benevento has a significant share of dairy farming but this share is much smaller than Parma. Avellino and Napoli share very little in terms of agricultural specialization with Parma instead. This behavior is reflected in the spillover effect. Caserta receives the largest long-run spillover effect from a shock in Parma followed by Benevento and Napoli. Avellino receives the smallest spillover effect instead. A major difference between spillover curves in Campania from those in close proximity with Parma is that in Campania they grow more slowly. Distance from the exogenous shock make the spillover effect much smaller but the peak of this spillover effect is reached only after four or five time periods. In NUTS3 units close to the source of the shock this spillover effect would take two or three years to reach its long-run level.

By computing the response of any i-th region to a shock in any j-th region, we can compute the three indicators of the spatial diffusion process presented in section 4: spillovers, spill-ins, and absorption capacity. These three spatial effects are here calculated for all NUTS3 regions and cumulated over a 20-year period window. Figure 7 shows the resulting maps. They suggest that the spatial diffusion process eventually involves the whole Italian territory though a denser effect can be observed in the regions of Pianura Padana, both because of their central geographical position and because of their specialization that tend to be repeated in many other regions of the country. On the contrary, however, there are regions that, due to their peripheral position and peculiar specialization, generate relatively little spillover and cumulate relatively little spill-ins. The balance of the two, however, goes in their favor as they eventually show a high absorption capacity.

To better detect the complexity of the spatial diffusion network implied by the adopted approach and the respective estimates, Figure 8 plots the correlation between the computed spillover, spill-in and absorption capacity of any NUTS 3 region and two different indicators of the underlying spatial weight matrix. The first simply is the number of links, that is, the number of the non-zero element expressing neighboring regions. The second indicator is the sum of the actual weights (i.e., elements) entering the spatial matrix before row-standardization. As already described, these weights depend on both the spatial links and the contiguity in terms of production specialization.

It emerges that, as expected, the correlation is positive for both spillovers and spill-ins. Nonetheless, the spatial structure implied by the matrix is significantly asymmetric as it clearly differs between the former and the latter. While spill-ins mostly depend on spatial contiguity, spillovers depend on the combined effect of both spatial and production contiguity. As will be stressed in the concluding section, this aspect is of major relevance since amplifying spillovers is critical to reduce disparities. Results would suggest that strengthening the production contiguity between the best and the worst performing regions may substantially increase the spillovers flowing from the former to the latter.

Another interesting consequence of this asymmetry of the spatial diffusion process emerges looking at the correlation coefficient of the absorption capacity. It is largely negative particularly when both spatial and production contiguity are taken into account. The interpretation is the following. Regions that are peripheral within the diffusion network (not only because they are geographically peripheral but also because their production specialization is peculiar) tend to show lower spillovers and spill-ins, but these latter ones are less affected by such marginality and this implies an advantage in relative terms: when a productivity shock occurs, they receive more than what they give. The opposite holds true for "central" regions and this makes these latter ones of main interest for a policy intended to reduce productivity differentials within the national agriculture.

7. Some concluding remarks and policy implications

As farming is a strongly site-specific activity, agricultural productivity may substantially differ across space also within a relatively small territorial scale. The objective of the present paper is to investigate the geographical dimension of agricultural productivity by identifying spatial clusters and measuring respective spillovers and spill-ins. Such an investigation requires a methodology not only making the spatial dimension explicit but also operating over a small and flexible enough geographical scale taking this site-specificity fully into account. The methodological approach here proposed seems suitable to provide interesting and rich information on productivity clustering and diffusion process over space. Future research may evidently improve this approach through alternative and more sophisticated definition of the spatial weight matrix as well as through improvements in the micro-level multilateral TFP calculation and in the dynamic space-time model estimated. Application and adaptation of the present approach to other farm-level data and agricultural contexts (for instance, at the EU scale) may also be helpful to better refine the proposed approach.

Beside the methodological issues, another aspect that is worth emphasizing about the approach and the results here obtained concerns their possible policy implications. As results suggest that a relevant diffusion process of agricultural productivity shocks occurs, the main implication is that whenever policies affect this process they also indirectly, and sometime unintentionally, affects spatial productivity differentials. As already emphasized by Esposti (2011), agricultural productivity differentials at least partially depend on permanent cross-regional heterogeneity due to non-transferable factors. Under the assumption that policies should aim at reducing productivity growth disparities, therefore, their main challenge is to generate forces that contrast or compensate such permanent heterogeneity.

This can be obtained in two different ways. First of all, by amplifying productivity spillovers. The free flow of knowledge and technology across territories can be improved by policies in different forms. On the one hand, trade-related spillovers are evidently favoured by measures making interregional trade easier and cheaper (infrastructural investments, for instance). Nontrade-related spillovers, on the other hand, depend on the interregional flow of information, knowledge and human capital. Policy-making may indirectly favour such forms of integration by funding technological and informational infrastructures as well as improving institutional capacity and collaboration. The methodology and the results here presented highlight that these spillovers do not necessarily second localized productivity clusters. Despite spatial contiguity, spillovers are amplified by regions' similarity in terms of production structure. As shown, for instance, a productivity shock occurring in the core of the (Northern) Italian agriculture may significantly affect also regions in the South showing a similar production specialization (dairy). Policies can thus contribute to create and strengthen knowledge and technology networks over the whole national space on specific agricultural productions.

When these supra-local networks are not feasible or not strong enough to reduce disparities, a second possible policy strategy concerns the role of public agricultural R&D investments and, specifically, the need for strengthening its public-good nature while restraining its region-specific character. In practical terms, in weaker territories policies may assume a compensatory role with specific measures in their favour. This can be achieved by either directing public agricultural R&D primarily toward these regions or favouring private R&D investments with selective measures (e.g., region-specific R&D tax incentives). Evidently, these policy implications deserve a much more careful design than what could be inferred by the present empirical study. Nonetheless, this further policy design effort definitely needs more spatially explicit evidence on agricultural productivity differentials and dynamics. The present study aims to contribute in this direction.

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Table 1. *Average multilateral TFP level and growth across different types of aggregation.*

Aggregation	*TFP index (mean.)*	*TFP growth rate (annual mean)*	*TFP growth rate (annual median)*
Macro-regions			
- North	1.010	-0.058	-0.069
- Centre	0.935	-0.014	-0.055
- South	0.998	-0.056	-0.050
Altitude classes			
- Plains	1.138	-0.059	-0.060
- Low-hillside	0.881	-0.025	-0.026
- High-hillside	0.651	-0.056	-0.097
Farm size			
- Small	0.467	0.008	-0.001
- Medium	0.925	-0.038	-0.037
- Large	1.219	-0.049	-0.029
Production specialization			
- Dairy	2.076	0.050	0.127
- Cereals	1.408	-0.009	-0.040
- Wine	1.757	0.010	0.026
- Horticulture	1.777	0.053	-0.021
- Fruits	1.867	0.011	-0.013
- Arable crops	1.574	-0.016	-0.023
- Granivores	0.608	0.068	-0.140
- Olives	1.695	0.026	-0.028
- Mixed	1.150	0.043	0.009
- Grazing livestock	0.764	-0.016	-0.046

Table 2. *Coefficient GMM, BCLSDV and ML-BCLSDV estimates of model (2a) (radial distance = 130 Km) – Standard error in parenthesis*

Estimator:	GMM	BCLSDV	ML-BCLSDV
Variable:			
$(\log \text{TFP})_{t-1}$	0.027	0.152***	0.080*
	(0.070)	(0.036)	(0.042)
$\mathbf{W}\ (\log \text{TFP})_t$	0.495*	0.219***	0.219***
	(0.295)	(0.075)	(0.075)
Extreme rainfall	-0.033	-0.052	-0.069
	(0.068)	(0.073)	(0.111)
Average altitude	-0.0004	-0.001**	-0.001
	(0.001)	(0.000)	(0.001)

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

Figure 1. *Multilateral average output (a) and input (b) indices (2008-2015 average)*

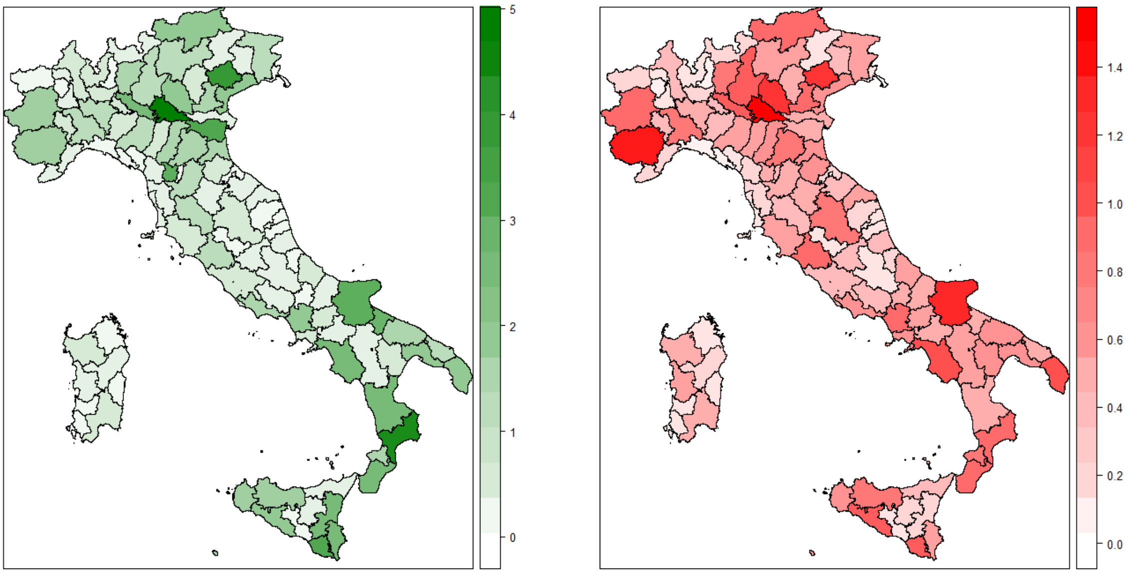

Figure 2. *Multilateral agricultural TFP index (2008-2015 average) (a) and average annual TFP growth rate (b)*

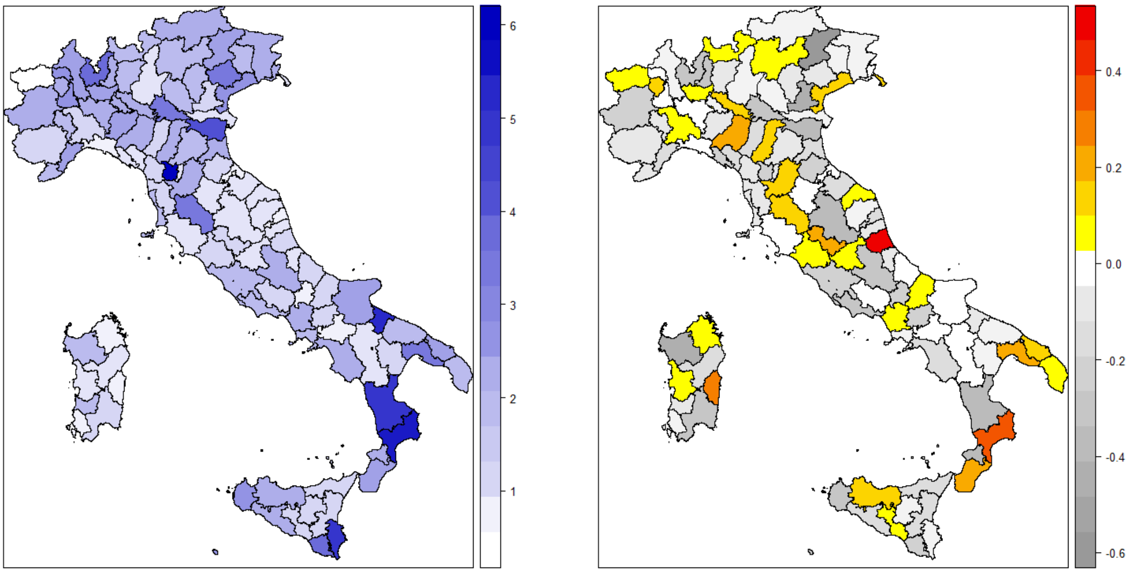

Figure 3. *Moran I test (left vertical axis) and its p-value (right vertical axis; $H_1: \delta > 0$) performed on the average TFP level with a variable definition of the neighboring space (the radial distance on the horizontal axis).*

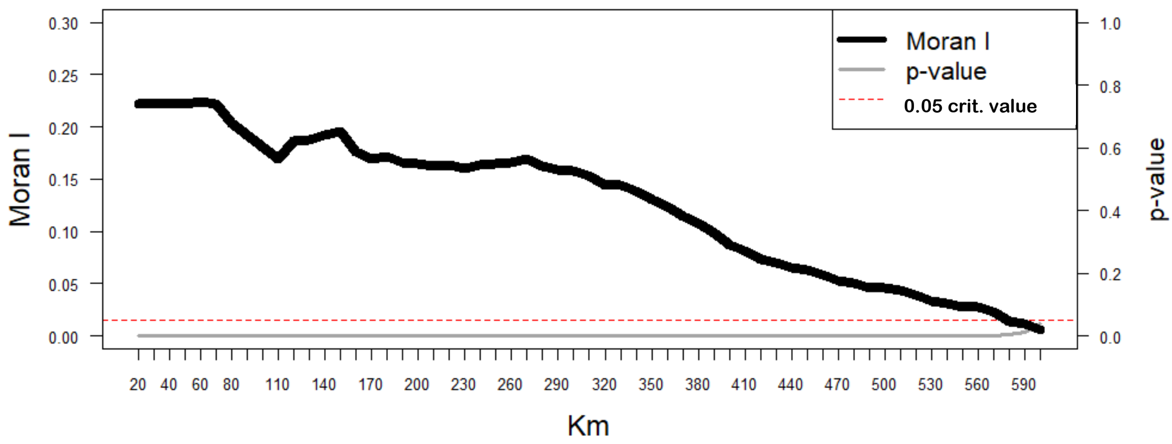

Figure 4. *Value of the concentrated log-likelihood function of model (2a) ML estimates with a varying radial distance in the spatial weight matrix*

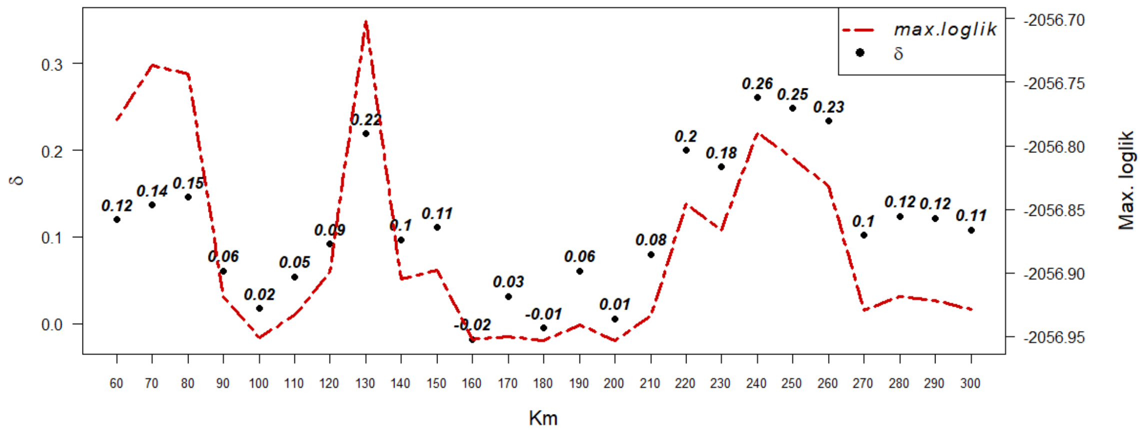

Figure 5*. Geographical representation of the shocks in Parma across space and over time: contemporaneous (t), after 1 year (t+1), 2 years (t+2) and 3 years (t+3) effect on the neighboring regions' TFP.*

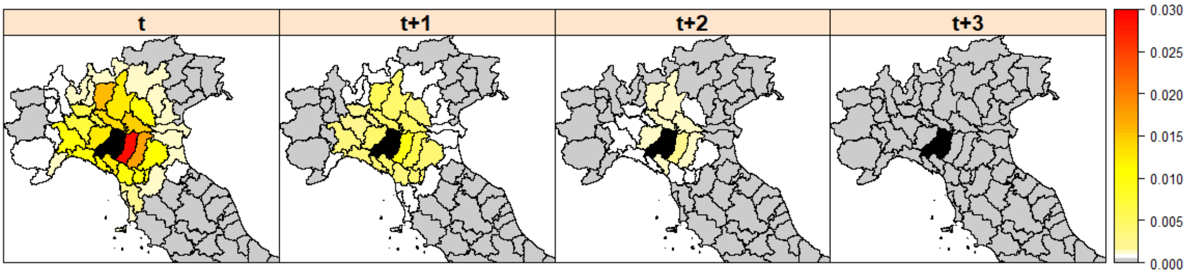

Figure 6. *Temporal evolution of the TFP contagion in Caserta, Benevento, Napoli and Avellino over 7 time periods*

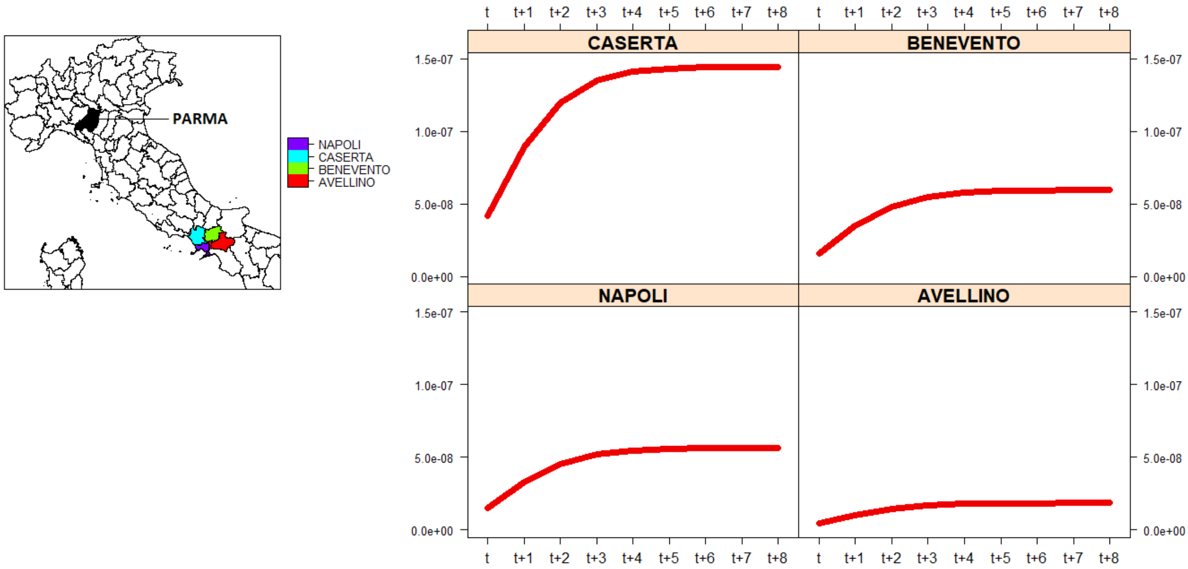

Figure 7*. Spillover, spill-ins and absorption capacity by NUTS3*

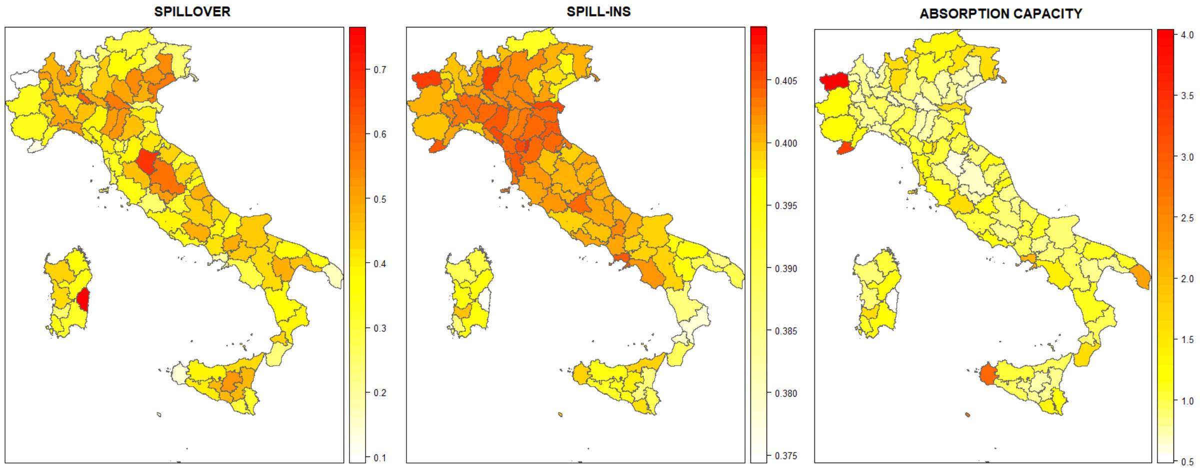

Figure 8*. Correlation between technological spillover, spill-in and absorption capacity and the spatial matrix structure (the same color identifies NUTS 3 regions belonging to the same NUTS 2 region).*