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Agricultural Productivity in Space

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Chapter 1

Introduction

This research is entitled *Agricultural Productivity in Space* because it deals with the measurement and analysis of agricultural productivity especially along its spatial dimension. It is called *in Space* because it describes agricultural productivity by means of multilateral comparisons at different aggregation levels and because it deals with the spatial properties of the measurements.

Multilateral comparisons are presented for geographical regions as well as for farm typologies and farm size classes. Their aim is to provide a wider perspective on the agricultural production performance in Italy.

The research uses the Italian FADN[1] survey data and thus, focuses on the Italian commercial agriculture as defined by the Italian FADN. Commercial agriculture is composed solely by farms that are considered large enough to provide a main activity for the farmer and a level of income sufficient to support his or her family[2]. Only farms that have an annual Standard Output equal or above 4,000 EUR enter the Italian FADN field of survey[3].

According to the Farm Structure Survey of 2013, commercial farms in Italy account for the 70% of the total number of farms, the 90% of the total Annual Working Units, the 94% of the total Utilized Agricultural Area and the 98% of the total Standard Output.

This research aims at providing measurements of agricultural productivity in Italy over the period 2008-2014 and at giving insights on its spatial properties. The specific research questions answered here are the following:

- What is the recent Italian agricultural performance ?

[1]Farm Accountancy Data Network. Rete di Informazione Contabile Agricola (RICA) in Italy

[2]http://ec.europa.eu/agriculture/rica/methodology1_en.cfm

[3]http://rica.crea.gov.it/public/it/campo_osservazione.php?action=cd_2010

    - How does the actual productive performance compare with the previously measured one ?
    - Are there regional disparities ?
    - Is there any relation between regional TFP and the composition of the agricultural sector within each region ?

- How does agricultural productivity behave in space ?
    - Is there productivity clustering ?
    - How does the TFP diffuse following a productivity shock?

To answer these questions, productivity measurements are derived at geographical level, at the level of types of farming and at the level of size classes.

At geographical level, measurements of productivity are derived at national level, at the level of FADN regions[4], and at NUTS3 level.

Exploiting farm-level heterogeneity and the detailed information contained in the FADN database, productivity measurements are obtained for the ten types of farming practices as classified by the Italian FADN. Farm type is a function of its Standard Output. It is defined as the crop or livestock product group for which its share of Standard Output is maximum[5].

Data are further aggregated and productivity measurements are derived for three farm size classes: small, medium and large. The size of a farm is defined as its economic size and, again, computed as a function of its Standard Output.

Agricultural productivity relative levels and growth rates are provided along each of the dimension and computed using the index number approach.

The index number approach is preferred over other methodologies because it provides a single measure of productivity that can be used to compare the production performance of different agricultural producing units over the period considered. In addition, the measures are relatively simple to derive, do not require the estimation of a production frontier, can be compared with measurements provided by international agencies and it can be used to answer the previous research questions.

Results at national level and at the level of farm typology and farm sizes point to a declining productivity in Italy over the period considered. Annual average growth rates are negative at country level. A declining performance is also observable for all the different size classes and the types of farming,

[4]FADN regional classification in Italy is similar to the NUTS2 classification by Eurostat. The only difference is the FADn classification splits Trentino-Alto Adige into two separate regions, Trentino and Alto Adige.

[5]http://ec.europa.eu/agriculture/rica/methodology2_en.cfm#tsotfs

except for the Wine sector[6]. Regional level performances show large variations within the period and across regions. The highest levels of productivity are observed in either the Northern regions and in some of the Southern ones. It is also shown that significant correlations exist between the composition of regional agricultural sectors and their regional performance.

Results are compared with the most recent calculation of agricultural productivity in Italy at regional level provided by Pierani (Pierani, 2009). It is shown that there are some similarities and stark contrasts between the results of the two researches. These difference might be due to an actual change in productive performance of Italian regions but also due to the differences in the data used and in the measurement approach.

In the second part of the research, the focus is on the spatial properties of the productivity measurement. Here, space-time dependence of productivity is inspected at the level of NUTS3 in the country. The granular level of analysis is useful to gain insights on the possible site-specificities of the agricultural production processes and to account for the large variability in topographic features, and in soil and climate conditions within the country.

The NUTS3 level is the most detailed spatial aggregation level that allows the systematic coverage of the Italian territory using the FADN sample.

A linear relationship between relative levels of productivity, its temporally lagged value, its spatial lag and other explanatory variables is hypothesized and estimated using the BCLSDV estimator. A selected estimated relationship is then used to model the diffusion process of a productivity shock hitting specific locations.

This research is important for, at least, three reasons. First of all, it contributes to the issues of food security and environmental sustainability in Europe. Secondly, it provides natural key performance indicators for the Common Agricultural Policy and provides insights for future CAP policy-making. Thirdly, it contributes to the debate on the possible slowdown of agricultural productivity growth in developed countries.

For what regards the contribution to the issues of food security and environmental sustainability, food security is defined at the 1996 World Food Summit as the physical and economic access at all time for all people, to safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life (FAO, 1996). Environmental sustainability is defined as the maintenance natural capital (Goodland, 1995). Productivity is defined as the amount of output produced per unit of inputs used (OECD,

[6]The Wine sector includes the production of common wine, quality wines and the production of grapes (http://www.rica.inea.it/public/it/disegno_campionario.php?action=ote_10)s.

2011). Increasing productivity contributes to the issues of food security and environmental sustainability in Europe because it either means:

- increasing the ability to produce the same amount of output with less use of resources;
- increasing the amount of output produced using the same amount of resources;
- both increasing output produced and resources used.

Anyhow, increasing productivity means contributing positively to the issue of food security lowering production costs and to the issue of environmental sustainability by using less resources.

Despite the fact that the analysis focuses solely on Italy, results are relevant also at a European level given then importance of Italian agriculture in Europe. According to the latest FSS (Eurostat, 2013), in 2013 Italy represents:

- the 9.3% share of the number of agricultural holdings in the EU-28;
- the 6.9% share of the total EU-28 Utilized Agricultural Area;
- the 7.2% share of the total EU-28 Livestock Units;
- the 8.5% share of then total EU-28 Annual Working Units;
- the 13% share of the total EU-28 Standard Output.

Thus, Italy represents one of the largest share of the European agricultural sector.

For what regards the ability to benchmark the Common Agricultural Policy, index numbers productivity measures can be used to evaluate the achievements of the objectives of the CAP in the latest financial framework 2007-2013 because:

- agricultural productivity growth is the first of the objectives of the common agricultural policy;
- index numbers productivity measures are one of the CAP impact indicators used by DG AGRI;
- the time span covered by the latest Italian FADN data collection spans the period 2008-2014 and covers almost completely the 7th financial framework.

The amount of money from the EU Budget poured into the Italian agriculture by the Common Agricultural Policy is large. On average, annually around 6.8 billion EUR are received by beneficiaries in Italy. In the period 2007-2011 the total CAP expenditure in Italy represented the 10.6% share of the total EU-27 budget (Bonfiglio et al., 2016). Productivity measurements could provide a measure of the return-on-investment of the CAP support.

The third main contribution of this research regards the additional support given to the debate on the possible slowdown of agricultural productivity growth in developed countries in recent years. The hypothesis of a slowdown in agricultural productivity growth was brought about after the international agricultural commodities price spikes of 2007/2008 and 2010/11 and the persistent price volatility since 2007. World food prices increased dramatically in 2007 and in the 1st and 2nd quarter of 2008. Afterwards, they fell dramatically but increased again during 2009 and 2010, peaking again in 2011 at a level slightly higher than in 2008.

Rising and volatile prices imply a tight market where supply is constrained and demand is growing. For a long time, during and after the Green Revolution, there have been a consensus over the ability of technology to cope with population and income growth. Science contributes to technical change and technical change is one of the main sources of productivity growth (Wang et al., 2015). Productivity growth has been regarded for long time the main contributor to output growth in agriculture (Ball and Norton, 2010). The changes in agricultural production were associated with major technological innovations that transformed the relationship between inputs and outputs in agriculture.

Recent price spikes have raised concerns over the ability of technology to keep pace with increasing demand, especially in developed countries and in the EU.

Empirical analyses have contributed to the debate giving contrasting views. In particular, measures of TFP growth produced by DG AGRI and by the USDA are completely different (Matthews, 2014). DG AGRI[7] estimated a TFP growth around 1.6% per annum from 1995 to about 2002 in the EU15. Since then, they claim that EU15-TFP growth has stagnated, growing only around 0.3% over the period 2002-2011. TFP growth in New Member States averaged around 1.6% growth per annum over 2002 and 2011. By country, higher TFP growth were achieved by New Member States (Matthews, 2014).

According to the USDA instead, agricultural TFP growth in the EU23 has been accelerating over the past decade. This acceleration has been particularly pronounced in the EU15, while TFP growth in the new MS has slowed down more recently. According to the USDA agricultural TFP growth rates for the EU23 were 2.1% for the decade 1991-2000, 2.2% for the period 2001-2005 and 3.1% for the period 2006-2010 approximately. The New Member States show a different pattern. The corresponding figures for the EU28 were 1.0% for the period 1991-2000, 1.2% for the period 2001-2005, and a 0.5% for the period 2006-2010. Over the first decade of the 2000s Italy, Portugal, Netherlands, Germany, Spain and Austria all had growth of 3% or more according to USDA (Matthews, 2014).

These difference in measurements between two prominent international

[7] Directorate-General for Agriculture and Rural Development

agencies can be due to the volume measure for the individual inputs and outputs to differences in weights used for aggregation, and to differences in the index number methodology adopted to create the TFP index (Matthews, 2014).

Additional references on international productivity comparisons in agriculture can be found in the work of the OECD entitled "Fostering productivity and competitiveness in agriculture" (OECD, 2011).

The present research can contribute to the debate by providing productivity measurements derived with a methodology similar to those used by the USDA and by DG AGRI but using different data. The FADN data are very detailed in respect to FAOSTAT and Eurostat data which were used by the two agencies. Therefore, they could provide a new point of view in supporting the previously presented researches and it could shed more light into what explains the difference between these two measures.

The research is divided into 6 parts. The second chapter is dedicated to the choice of productivity measurements. Several methodologies for the estimation of productivity are presented. Index numbers in a panel data context are discussed and their choice as productivity measurements is justified. The third chapter implements the index number methodology in a panel data context to derive relative productivity measurements for the Italian agriculture. The fourth chapter uses productivity measurements derived at the NUTS3 level in order to analyze the spatio-temporal properties of productivity and to model the diffusion process of TFP. The fifth part summarizes and discusses the results obtained in the third and fourth chapter. The last part is constituted of a series of important annexes. Here, the features of the sampling plan as well as the data processing steps used in the derivation of the indexes are described.

Chapter 2

Productivity measurement approaches

In Chapter 3 and Chapter 4 aggregate productivity measures are derived at different aggregation levels. Multilateral comparisons in a panel data context are presented at regional level, for NUTS3, for types of farming and for size classes of farms. The final objective is to give a wider perspective on the Italian agricultural production performance.

The present chapter provides the theoretical background for the measurement of productivity. It focuses on the choice of the productivity measurement methodology used in the next chapters and on the available alternatives. It starts with the definition of productivity.

Productivity is defined as how well an economic system converts input into desirable outputs (Fuglie et al., 2016). The concept of productivity is often understood as a ratio of output to a single input. A typical example in agriculture is land productivity, i.e., the ratio between a measure of output and the surface of land utilized in the production process. Such a productivity measure, like any other that takes into account a single factor of production, is referred to as partial productivity measure because it takes into account solely a single factor of production.

Such a productivity measure might give a biased representation of the comparisons between agricultural production processes. The reason is that, land productivity might be low (or high) due factors such as a low (or high) amount of fertilizers applied or little (or much) labor employed on-site. Missing this kind of information might lead to biased conclusions.

In the present analysis, the term productivity refers to a measure of Total Factor Productivity (TFP), i.e., a measure that takes into account of all - or, at least, as many as possible - the outputs and inputs of the production process that are marketed. Such a measure is generally defined as a ratio of aggregate output to a ratio of aggregate input:

$$TFP = Y/X$$

If the production process was single-input and single-output, and the input and the output were homogeneous, then a simple ratio Y/X would suffice in providing information regarding the production performance of every single unit. In such a case, the Partial Productivity measure would coincide with a measure of Total Factor Productivity.

However, agricultural production processes, especially at an aggregate level, are multi-input and multi-output. It is necessary to use some multi dimensional function in order to describe and compare complex production processes that might substantially differ among each other.

The tool that is most widely used in economics to describe a production process is the concept of production function. The production function is a mathematical function that formalizes the relationship between inputs and outputs. The evolution of the production function that best suits the multi-dimensional nature of the agricultural production process is the concept of distance function. A distance function can be input or output orientated. An input distance function characterizes the production technology by looking at the minimal proportional contraction of the input vector given an output vector. An output distance function considers a maximal proportional expansion of the output vector, given an input vector (Coelli et al., 2005).

Distance functions can be used to derive the Malmquist productivity index, i.e., the basis for most productivity analyses[1]. The Malmquist index is purely a theoretical index introduced by Caves et al (Caves et al., 1992).

There are two general approaches through which the concept of the Malmquist index can be made operational. The first one uses the idea of comparing the output distance functions of different units or period of time. Alternatively, the input distance functions could be used. The second one, called Hicks-Moorsteen approach uses both output and input distance functions instead. In the present analysis, the second approach is used. A TFP index is constructed as a ratio of two geometric averages, on the nominator the geometric average of two output Malmquist indexes and on the denominator the geometric averages of two input Malmquist indexes. Each component of the ratio is approximated by using the Fisher index number formula.

The Fisher output and input quantity indexes provides an approximation to the Malmquist theoretical indexes. It can be proven that if the distance

[1]There exist also generalization of distance functions such as the Directional Distance Functions and Hyperbolic Distance Functions but we will not talk about this methods here

functions used in the derivation of the Malmquist index are quadratic functions with identical second-order parameters, then the geometric average of the Malmquist indexes is equal to the Fisher index (Coelli et al., 2005). Thus, the HM TFP index is closely related to the Malmquist index.

So, index numbers provide a theoretically meaningful aggregation method for inputs and outputs while avoiding strict assumptions regarding the shape of the production technology frontier. Van Biesebroeck (Van Biesebroeck, 2008) defines the advantages of the index number procedure in the context of productivity analysis as the ease with which one can access productivity measures that are robust to the assumptions of the functional form of the underlying production technology. The main disadvantages instead are the deterministic nature of the approach and the assumptions of optimizing behavior and competitive market structure needed to justify their theoretical basis.

The HM approach using index numbers is a so-called non-frontier deterministic approach to productivity measurement and it is different from other approaches. The other most widely used alternatives are based on the comparisons between producing units after the estimation of a technology frontier. These alternatives can be either deterministic in nature or stochastic allowing for the presence of noise in the data.

The HM approach with index numbers is preferred here over the other available approaches because it allows the derivation of theoretically meaningful indexes without the need to estimate the parameters characterizing the technology. So, it is much simpler and allows to focus on the complexity of the dataset.

The non-frontier approach is a widely used method to measure agricultural productivity and is used by the major statistical offices around the world. The USDA, DG AGRI and the OECD all derive productivity statistics using this methodology. Their estimates are also at the core of the debate on the existence of an agricultural productivity growth slowdown in recent years.

The other approaches to productivity measurement are based on the concept of either a output-orientated Malmquist index or an input-orientated Malmquist index. These approaches require the analyst to estimate the full production technology characterizing the production process.

Knowing the production frontier allows the derivation of the Malmquist indexes as a function of the distance to the frontier. On top of that, Malmquist indexes derived using this approach allows the decomposition of productivity change into its sources. Using only quantity information it could be possible to attribute the change in the Malmquist index to a change in technology and a change in efficiency by which the technology is used.

Such approach is made operational typically in two ways one of which is parametric and the other non-parametric. The first one is the Stochastic Frontier Analysis while the second approach is called Data Envelopment Analysis. Both ways provide more information with respect to the index number approach. At the same time however, they introduce complexities in the measurement process. Also, it can be proven that under certain conditions the two approaches coincide with the HM and index numbers approach.

Despite the disadvantages of index numbers and the HM approach, this methodology is used here to derive output and input aggregate indexes and to approximate the Malmquist indexes. Using index numbers, an output index is created by aggregating together quantities of different output by weighting them using their value shares. An input index is created by aggregating together quantities of all the inputs employed in the production process by weighting them by their cost shares. The two quantity index are then divided to obtain a productivity index.

It can be proven that the derived output, input and productivity indexes satisfy several interesting statistical properties (Fisher, 1922). The property that none of the productivity measurements mentioned here satisfies is the property of transitivity: a set of bilateral comparisons might not be internally consistent. This is an extremely important property to be satisfied in cross-sectional and panel comparisons as it guarantees the uniqueness of the productivity measurements (Hill, 2004).

In order to derive indexes that can be compared over time and across units, it is necessary to augment the index number methodology in a way that it satisfies the transitivity property. In the present research, transitivity is achieved by means of chaining bilateral comparisons in a spanning tree that minimizes the Paasche-Laspeyres spreads between the nodes composing the tree. This procedure allows for the derivation of indexes comparable over time and across producing units. The indexes at regional level, at the level of NUTS3, for types of farming and for size classes are derived using this procedure. Productivity indexes at national level are derived using a chained Fisher index instead.

This chapter presents the theoretical Malmquist index and the ways by which it can be made operational. Index numbers and the Fisher formula are introduced first. Then the minimum spanning tree transitivization method is presented together with alternatives for the creation of panel robust indexes. Subsequently, the alternative productivity measurement methodology, that is, Data Envelopment Analysis and Stochastic Frontier Analysis are briefly introduced and compared with the HM and index numbers approach.

2.1 Malmquist index

The Malmquist index is based on the concept of Shephard distance functions and describes a measure of productivity change. The Shephard distance function can be thought of as a generalization of the concept of production function. It accommodates for a multi-input multi-output production processes. The Output Shephard Distance function is defined as follows:

$$D_o(x, y) = min \left\{ \theta : \left(x, \frac{y}{\theta} \right) \in T \right\}$$

where T is the state of technology, x the input vector and y the output vector. As an example, the Malmquist index using the output distance function between two adjacent periods will be derived assuming that technology stays the same in the two periods.

By definition, the output distance function is homogeneous of degree +1 in outputs. Following the exposition in Fried et al. (Fried et al, 2008), in Figure 2.1 and Figure 2.2 the concept of distance functions is graphically presented:

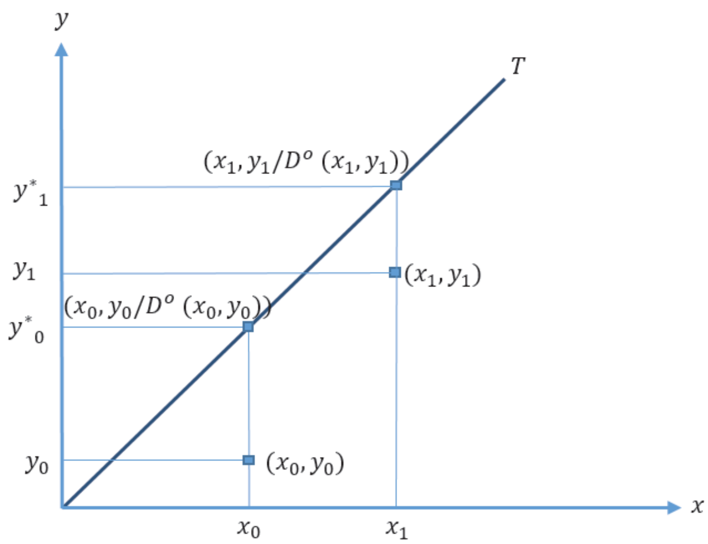

Figure 2.1: Productivity and distance functions (1)

The technology T is bounded above by the ray from the origin and, given free disposability, from below by the x-axis. Two sample outcomes (x_0, y_0) and (x_1, y_1) are projected onto the reference technology by the output distance function in the output direction. The slope of the ray passing through

(x_1, y_1) is larger than the other one thus, productivity is higher for observation (x_1, y_1).

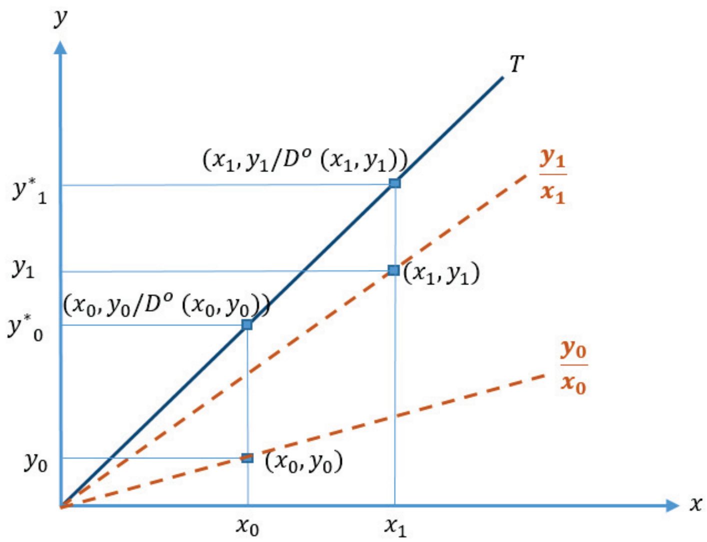

Figure 2.2: Productivity and distance functions (2)

Distance functions can be used for multiple outputs and multiple inputs and, the productivity index as ratios of output distance functions provides a generalization of the average product ratios. This average product ratio is the definition of the Malmquist index:

$$M_o = \frac{D^o(x_1, y_1)}{D^o(x_0, y_0)}$$

In the case of two periods of time or two cross-sectional comparisons, it is likely that the technology T would be different in these two situations; we would probably have a T_0 and a T_1 that differ from each other. In such a case, both technologies could be used as reference technology for making comparisons. Since no preference between the two exists, it was decided to define a productivity index as the geometric average of the two:

$$TFP_{01} = \sqrt{M_0^o * M_1^o} = \sqrt{\frac{D_0^o(x_1, y_1)}{D_0^o(x_0, y_0)} * \frac{D_1^o(x_1, y_1)}{D_1^o(x_0, y_0)}}$$

The Malmquist index is a theoretical index and is typically made operational using non-frontier or frontier approaches. The first way is the index number approach. It a so-called a non-frontier method because it does not require the estimation of a reference technology. With this method, output and input comparisons are made assuming that producers are technically and allocative efficient. If the data is assumed to be noise-free, that measure can be interpreted as a measure of technical change. However, if one if willing to make the additional assumption that the distance functions can be represented by quadratic functions, than the approximation to the Malmquist index would be exact by using the Fisher formula as index number formula.

The second way is the frontier approach. Under this approach, the focus is on the comparisons between the performance of producing units using a common technology frontier. The technology frontier is the best-practice surface that is estimated from the data and used to compare production performances by inspecting the extent to which producers fail to reach that frontier. The frontier approach can be used in two ways. In the first way, the assumption is that there is no noise in the data and that the failure to reach the frontier is entirely due to technical inefficiency of producers. This is the deterministic frontier approach. The second way allows for noise in the data and assumes the frontier surface as stochastic.

The frontier approach is a more sophisticated way to implement the Malmquist index with respect to the non-frontier approach. The data is used to fully describe the technology. The comparisons of production performances against a frontier allows an implementation of the Malmquist index that includes the descriptions of its sources of growth:

- technical efficiency;
- technical change.

However, the estimation of a full technology poses some conceptual and statistical challenge that introduces complexities in the analysis.

In this research the focus is on the micro-nature of the data and, the HP approach through index numbers is preferred over the other available ones.

2.2 Hicks-Moorsteen TFP Index

The present research uses the Hicks-Moorsteen (Coelli et al., 2005; Fried et al., 2008) approach to derive space-time comparable productivity measures for each level of analysis. This approach is fairly easy and is based on a ratio of the geometric average of two output Malmquist indexes and the geometric average of two input Malmquist index.

$$\textbf{HM TFP Index} = \frac{QI_{st}^{output}}{QI_{st}^{input}} = \frac{\sqrt{M_s^{output} * M_t^{output}}}{\sqrt{M_s^{input} * M_t^{input}}}$$

The Malmquist indexes are approximated using the Fisher index number formula:

$$\textbf{HM TFP Index} = \frac{\textbf{Fisher output quantity index}}{\textbf{Fisher input quantity index}}$$

The Fisher index is exact for the geometric mean of the theoretical Malmquist index when the technology is a quadratic functional form. As the quadratic function is a flexible function, the Fisher index is called *superlative*.

Index Numbers and the Fisher formula

Index numbers are defined as functions that measure changes of a set of prices and quantities over time and/or across a number of units (Coelli et al., 2005). There are several index numbers formulas. The most widely used are the Laspeyres, Paasche, Fisher and Tornqvist formulas. In the present research, output and input quantity index are derived using the Fisher formula.

Given vectors of prices p and quantities q for two time periods and/or units s and t, the Fisher index is defined as follows:

$$QI_{st}^{Fisher} = \sqrt{\frac{p_s^{'}q_t}{p_s^{'}q_s} * \frac{p_t^{'}q_t}{p_t^{'}q_s}}$$

Index numbers are typically chosen on the basis of their statistical properties and on the basis of their economic foundation.

For what regards the statistical properties of indexes, the Fisher formula is the index number formula that satisfies most of the statistical tests available to compare such indexes. These tests, proposed by Fisher (Fisher, 1922), are the following:

- *Positivity*: the index should be everywhere positive;
- *Continuity*: the index is a continuous function of price and quantities;
- *Proportionality*: if all quantities increase by the same proportion than the index should increase by that same proportion;
- *Dimensional Invariance*: the quantity index must be independent of the units of measurement used in the analysis;
- *Time-reversal test*: for two periods s and t:

$$QI_{st} = \frac{1}{QI_{ts}}$$

;

- *Mean-value test*: the quantity index must lie between the respective minimum and maximum changes at the commodity level;
- *Factor-reversal test*: it requires that multiplying a price index and a volume index of the same type should be equal to the proportionate change in the current values;
- *Transitivity*: for any three periods and/or units s, t and r this test requires that:
$$QI_{st} = QI_{sr} * QI_{rt}$$
.

The Fisher index is the only index that satisfies all the properties listed above with the exception of the circularity, or transitivity, test. In fact, no index number formula satisfies the circularity test.

To make an index number comparable across-spatial units it is necessary to derive it using specific procedures. These procedures will be discussed in the next session.

For what regards the economic foundation of the index number formulas, the Fisher index is called *exact* for a quadratic aggregator function. An index number is *exact* for an aggregator function, i.e., it is consistent with an aggregator function, when it is equal to the ratio of two aggregator functions computed using the same price and quantity information. Because the quadratic production function is a flexible production function, and the Fisher index is exact for a quadratic function, the Fisher index is called *superlative* (Diewert, 1992).

The necessary hypotheses to be made in order to derive the economic theoretic properties of the index number formulas is that production is technical and allocative efficient.

2.2.1 Panel comparisons using index numbers

Standard index number formulas, either fixed-based or chained, satisfy many statistical properties except for the transitivity property. Following Hill (Hill, 2004) this property can be formulated as follows:

$$QI_{js,kt} = QI_{js,mu} * Q_{mu,kt}$$

and it 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 comparisons via unit m in time period u.

Because of the failure to satisfy this statistical property - except in cases in which the weights attached to each item in the derivation of the index number formula is the same for all producing units - the standard index number algorithms are not suitable for making productivity comparisons in time and across producers. The main issue with the lack of transitivity is that more than one estimate could be derived from the measurement (Hill, 2004).

The solutions adopted by the literature to solve this comparability issue are based on two different methods. The first method is based on the idea that indexes can be derived by comparing all units under analysis simultaneously (Rao et al., 2010). This is the EKS approach. Under this approach a first set of non-transitive index numbers are derived using the standard formulas. Then, in a second step, these measures are transformed in such a way that the matrix of all comparisons satisfy the transitivity property while minimizing the deviations from the original index (Rao et al., 2010). This approach is one of the most widely used in the literature of productivity measurements in agriculture. It is especially used by statistical offices such as the OECD, DG AGRI, Eurostat and the USDA to derive space-time comparable price index statistics. The main issue with this methodology is that it considers all binary comparisons as equally reliable. However in agriculture, as it is true also for many other economic sectors, it is well known that some comparisons are more reliable than others. Reliability stems from the similarity of the production processes. Productivity comparisons are certainly more reliable when two similar production structures are compared with each other rather than when comparing two dissimilar ones.

Because of the failure of the EKS transitivity procedure in recognizing that production structures differ from each other, the present analysis favors a second approach in the derivation of transitive index. In contrast to the EKS procedure, this second approach is based on the idea that comparisons across a set of producers over time can be made by chaining together bilateral comparisons that are selected based on the similarities of their production processes. This method is called *minimum spanning tree* approach and requires the selection of a set of bilateral comparisons to be chained together. To satisfy the transitivity property, the chain of bilateral comparisons must contain no cycles. In other words, the set of bilateral comparisons should represent a spanning tree. The set of bilateral comparisons is established through a specific procedure that identifies the pairs of most similar production structures based on their similarities in prices and quantities. The similarity measure used to identify the set of bilateral indexes is the Paasche-Laspeyres spread (Hill, 2004):

$$PLS_{js,kt} = \left| \log \left(\frac{QI^{L}_{js,kt}}{QI^{P}_{js,kt}} \right) \right|$$

Thus, the indexes are obtained by chaining bilateral comparisons across a spanning tree that is the spanning tree that minimizes the global distance between the nodes of the tree where this distance is defined as the Paasche-Laspeyres spread:

$$min \sum_{edge=1}^{K-1} PLS_{edge}$$

Because the method is based on the idea that comparisons should be made between similar producers, the minimum spanning tree chaining method is seen as a major development with respect to the EKS procedure in the derivation of transitive index numbers (Rao et al., 2010). The spanning trees used to construct the transitive output and input quantity indexes are represented in Appendix C and Appendix E.

Trade-offs when indexing in time and space

In panel data comparisons, a tension exists between the spatial and temporal dimension (Hill, 2004). The tension can be described using five criteria: temporal fixity, spatial fixity, temporal consistency, spatial consistency and temporal displacement. Hill (Hill, 2004) has proposed different methods to generate a set of panel robust indexes and evaluate them based on these criteria.

Temporal fixity is respected by a panel comparison whenever the set of comparisons derived in a panel dataset are not affected by the inclusion of a new temporal data observations.

Spatial fixity is respected whenever the set of comparisons derived in the panel dataset are not affected by the inclusion of the information regarding a new producing unit.

Temporal consistency is respected if the panel comparison is units separable, i.e., if the overall comparisons can be broken up into a series of separate temporal comparisons for each producers that are linked together. This means that the temporal results for each producer do not depend on the other producers in the comparisons.

A panel comparison is *spatially consistent* if it is time separable, i.e., if the overall comparisons can be broken up into a series of separable spatial comparisons for each year. This means that the spatial results for each year do not depend on the other years in the comparison.

Temporal displacement measures the time span between time periods represented in the formula of bilateral spatial comparisons subsumed within a panel index comparison (Hill, 2004). The units of temporal displacement are the same as the intervals between time periods in the panel data set. Temporal displacement of a panel comparison is the maximum temporal displacement of each of the bilateral spatial comparisons within it.

Hill (Hill, 2004) proposed six panel comparisons methods and evaluated them using these criteria.

The *minimum-spanning-tree* considers each vertex of the tree as a space-time observation. The total number of vertexes in the tree is given by KT where K is the number of producing units and T the number of time periods. The spanning tree is selected based on a defined distance function. In the present research, this method is adopted to generate panel robust productivity indexes and the Paasche-Laspeyres spread is used as distance function. This method violates spatial and temporal consistency, and temporal fixity. Still, it is favored because is based on the idea of comparing production units with similar production structures and is robust to the choice of the reference space-time observation. As this research is mostly based on the cross-sectional dimension of the data, this method seemed to be the most appropriate choice.

Minimum-temporally-fixed-graph is a method that constructs the graph in a series of steps. The first step consists in making a multilateral comparison using the EKS method for the first year of the panel. Then the vertexes for the following year are connected to those of the previous year by the minimum-spanning tree method and so on for every year of the panel. Using this method, temporal fixity is respected while temporal consistency and spatial consistency are not.

Temporally-consistent graph consists of a linkage between separate temporal comparisons for each producing units. A temporally consistent graph is obtained by linking together all these temporal comparisons. Temporal consistency and temporal fixity are assured. Spatial consistency is violated.

Spatially-consistent graph consists in a series of multilateral comparisons long as the number of time periods in the analysis. The spatial comparisons are made for each of the year and then linked together though a chronological unit of a single producing unit. The method violates temporal consistency but satisfies spatial consistency and temporal fixity.

A *temporally-fixed grid graph* is constructed from purely spatial comparisons and purely temporal comparisons. Thus, the graph has a grid structure. EKS spatial comparisons are made at a certain time interval, and temporal comparisons are made using chronological chains, except in the year in which the EKS comparisons are made. This method violates temporal consistency and spatial consistency, unless the EKS procedure are made every year. Temporal fixity is satisfied.

Lastly the *multilateral* method uses trasitivization algorithm such as the EKS is applied to the whole panel of comparisons. The method violates temporal consistency, spatial consistency and temporal fixity.

No consensus has emerged over which method is better to generate panel robust comparisons. The decision of the minimum spanning tree was taken here because it is a practically easier procedure in respect to the minimum temporally fixed graph and the temporally fixed graph, because it is based on the similarity of production structures of the space-time units involved in the comparison, because it is not sensitive to the choice of benchmark space-time unit unlike other methods such as the temporally consistent graph or the spatially consistent graph.

2.3 Data Envelopment Analysis

It is a frontier, deterministic, non-parametric method for measuring productivity. It uses a measure of distance from the observed performance of each producer to the estimated frontier and it uses this distance to compare them in terms of efficiency. Any deviation from the frontier is attributed solely to technical inefficiency. No room is made for the assumption of statistical noise in the data.

A short definition of DEA is that it provides a mathematical programming methods for estimating best practice production frontiers and evaluating the relative efficiency of different entities (Bogetoft and Otto, 2011).

The non-parametric nature of the methodology is its main advantage and makes it easier to implement with respect to the frontier parametric methods.

DEA approximates the unobservable production frontier by wrapping with a convex hull the data on observed productions of entities.

The frontier T is approximated using the *minimal extrapolation principle* (Bogetoft and Otto, 2011) where T^*, the estimated frontier, is constructed as the smallest subset of the and output space that contains the data, and satisfy the returns to scale assumption characterizing the technology.

The basic assumptions in DEA are the following:

1. *free disposability*;

2. *convexity*;

3. *return to scale*;

4. *additivity*.

The distance measure in a DEA context can be directly calculated using four linear programs for each producer in the panel. One issue that was recognized in DEA frontier estimation is the presence of slacks.

The slack problem is when a firm is placed onto the vertical or horizontal part of the estimated frontier. In such cases, the entity is considered as technically efficient as it lies onto the frontier but still it could improve its situation by producing more output (or by using less input if it lies onto the horizontal part of the frontier).

The two solutions proposed in these cases are: using a penalty factor for slacks that is large enough to recognize the possible slack and small enough not to alter the numerical results; to solve the dual problem using strictly positive input and output prices.

By using panel data, it is possible to replicate the analysis in each of the accounting period of the analysis and derive the corresponding Malmquist index. The presence of the frontier allows to split the change in the Malmquist index into a change in the technological frontier by looking at the shift of the estimated frontier and into a change in technical efficiency, i.e., how much the failure to achieve the frontier of best practices has changed over adjacent periods.

According to Van Biesebroeck (Van Biesebroeck, 2008) the main advantage of DEA is the absence of functional form or behavioral assumptions. Disadvantages are the deterministic nature of the methodology which makes the measurement sensitive to even one outliers for one of the entity under investigation and the problem of estimating the efficiency for some particular firms. Under variable returns to scale or example, each firm with the lowest input or output level in absolute terms is also fully efficient.

2.4 Stochastic Frontier Analysis

The other most widely used approach for implementing the Malmquist productivity index is the Stochastic Frontier Analysis. This methodology is particularly complex but informative.

It is a frontier, stochastic, parametric method. It extends the literature of the econometric estimation of production technologies with deterministic frontier allowing the presence of statistical noise in the data.

In the literature of deterministic frontiers, the most widely used estimation methodologies were OLS, COLS and MOLS estimation of production or distance functions. The first one focuses on the estimation of the technologies parameters associated with a function passing through the data. This methodology is not consistent with the idea that the production frontier is the frontier of the production possibility set. To be consistent with this idea, the second method extends the first by shifting the estimated regression line accordingly and wrapping up all the observations. The deviation from the frontier is defined as technical inefficiency. The MOLS approach uses the OLS procedure to derive a regression line in the first step. In the second step, it uses the methods of moments and assumptions regarding the distribution of the inefficiency terms to derive inefficiencies for each producers. All the three specification can be extended to include a time trend to take into account of possible shifts in the production function due to technical change in panel data settings. The main problem with this methodologies is that they do not account for noise in the data.

SFA is a major evolution of these methodologies as it allows the derivation of a frontier function consistent with the idea that the production frontier represents the set of maximum production possibilities and by introducing noise in the model. Noise is introduced by a composite error term that includes a technical inefficiency term and a random noise term. The noise term is a typical random component designed to capture the effects of random exogenous variations in the operating environment (Kumbhakar and Lovell, 2008). The inefficiency term is a one sided error component designed to capture the effects of inefficiency and constitutes the main contribution of SFA to the literature of production analysis (Kumbhakar and Lovell, 2008).

SFA originated from two papers published nearly simultaneously by Meeusen and van den Broeck (Meeusen and van den Broeck, 1977) and Aigner, Lovell, and Schmidt (Aigner et al., 1977). They shared the composite error structure that can be analytically expressed in a production function context as follows:

$$y = f(x; \beta) * exp(v - u)$$

where y is a scalar output, x is a vector of inputs and β is a vector of technology parameters. The first error component $v \sim N(0, \sigma_v^2)$ is intended to capture the effects of statistical noise, and the second error component $u \geqslant 0$ is intended to capture the effects of technical inefficiency (Kumbhakar and Lovell, 2008).

Thus, producers operate on or beneath their stochastic production frontier $f(x, \beta) * exp(v)$, according to the value of u. If $u = 0$ then the producer operates on the production frontier while, if $u > 0$ there is a certain degree of technical inefficiency (Kumbhakar and Lovell, 2008).

After the estimation of the composite error term it is possible to decompose it into its two components thanks to the work of Jondrow (Jondrow et al., 1982) in which the authors proposed the expected value $E[u|v-u]$ as solution to the problem of disentangling the error component to the inefficiency term.

The estimation of such a model in a panel data setting could be done using a fixed-effect or random-effect estimator without the need to specify a specific distribution for the inefficiency term thus reducing the number of hypothesis to be made. If one is willing to specify a distribution for the error term than, it is also possible to use the maximum likelihood estimator to obtain estimates of technical efficiency and estimates of the other parameters of the model.

In a panel data setting, it is also possible to specify a time-varying inefficiency term and a time trend to capture the shift over time of the stochastic production frontier. There are various approaches to the estimation of a time-varying technical efficiency. No consensus has yet emerged over which method is superior and the choice often depends on the analyst.

The SFA allows the full estimation of a production technology, it allows the full description of the production process and to decompose the Malmquist index into its constituent components namely technical efficiency, technical change, scale efficiency and allocative efficiency. Thus this approach is very informative. However, this advantage comes at a high cost.

There are great challenges to the estimation of production frontiers. The two main challenges are statistical issues such as functional form specification, and theoretical ones such as endogeneity and distributional assumptions.

2.5 Concluding Remarks

In this chapter a set of the most widely used methodologies have been briefly review. To date, no clear consensus has emerged over which methodology is best for productivity comparisons. Every methodology has its own advantages and disadvantages. Much of the decision in empirical analyses is based on the specific data availability, the objective of the analysis and the assumptions one is willing to make.

In the present study, the HM approach with index numbers was selected as a tool to derive productivity comparisons over time and across different producing units. This methodology was favored over the DEA and the SFA because of its simplicity and comparability with the literature on agricultural productivity at national and international level. The index number procedure is the simplest approach among the three reviewed. It is simple because it requires a one-step only: the derivation of transitive index numbers. DEA and SFA would require a multi-step approach in order to derive panel consistent measures of productivity. First, they would require hypotheses on how to aggregate the large number of outputs and inputs into a meaningful number of aggregate statistics. Then, the parametric or non-parametric estimation strategy would be required to derive Malmquist indexes of productivity. Thirdly, a transitivization method such as the EKS would be needed to create panel consistent comparisons. The simplicity of this method allows us to avoid the complexity of a multi-step measurement approach and focus attention on the structure of the database.

A major challenge of this work consisted in the compilation of the required price and quantity statistics from the FADN farm-level data. Much of the attention have been devoted to the inspection of the data, the understanding of its features and to pre-processing steps needed to derive price and quantity statistics. The index number approach was considered to be the best choice in these circumstances. All the same, it would be interesting to extend the scope of the analysis by using and comparing productivity measurement with the alternative approaches.

Equally interesting would be the extension of the analysis in order to take into account of the environmental impacts of economic activity. Such an objective requires the inclusion of undesired outputs and consumption of natural resources into the measurement. An SFA framework would probably be the best way to pursue such extensions. An SFA framework would allow the inspection of a multi-output technology while introducing hypotheses on the relationships between output, bad output, marketable and non-marketable inputs. An alternative approach would require the development of sets of agri-environmental indicators and present them alongside typical measures of TFP (Fuglie et al., 2016).

Chapter 3

Agricultural productivity in Italy over the period 2008-2014

3.1 Introduction

In this research, multilateral productivity comparisons for regions, for types of farming and for economic size classes of farms are presented to describe the agricultural production performance in Italy over the period 2008-2014.

Productivity measurements are derived using the index numbers approach and the Fisher formula. In order to make productivity statistics comparable across spatial units and over time, indexes are constructed using the minimum spanning tree method proposed by Hill (Hill, 1999; Hill, 2004). In this procedure, transitivity of indexes is achieved by chaining bilateral comparisons in spanning trees where the vertexes are all the space-time units and the edges are Fisher bilateral comparisons.

The main contribution of this research is the derivation of productivity statistics at regional level in Italy together with productivity statistics for the different types of farming and for size classes of farms. The derivation of productivity indexes at regional level and at the level of types of farming and size classes were made possible by the use of farm-level data and by leveraging farm-level heterogeneity. Price and quantity information for each level of analysis are obtained by aggregating weighted farm-level price and quantity statistics to the desired level of aggregation. The data used are taken from the Italian FADN database. This contains survey information on annual samples of around 11,000 farms defined as commercial farms. Thus, the research focuses on the professional side of the Italian agricultural sector and excludes the very small-holding farming practices.

The use micro data posed three main methodological challenges. First of all, not all the necessary information for the derivation of output and input indexes were readily available in the Italian FADN tables. Missing information, such as the unit price of production, the price of family labor and the price and quantity of capital services, had to be imputed for all farms. Other information such as the price of fertilizers and pesticides for all time periods considered, and such as the opportunity cost of investing in durable assets had to be imported from additional data sources such as Eurostat or the European Central Bank.

Secondly, the information contained in the FADN database regarding products produced and reused on-site by farms is very large. Collectively, more than a thousands crop and livestock products are recorded. Because input and output comparisons are based only on the items shared by two adjacent units, such a large number of products might lead to comparisons between units involving only a small fraction of their total production. In addition, dealing with very large output and input matrices poses serious computational challenges. Thus, to simplify the construction of aggregate indexes and to make bilateral comparisons across space-time units more meaningful, a specific products aggregation procedure based on the results of the minimum spanning trees was used. This procedures consists in aggregating similar products by taking into account their characteristics and units of measurement.

Thirdly, there was a need to derive aggregate price statistics from weighted farm-level information. This is achieved here by means of production-weighted average prices for each level of aggregation.

Results show that Italian productivity is declining over the period 2008-2014. The aggregate productivity performance at country level is a mixture of very different performances at regional level. Two productivity regional clusters, one in the North and one in the South were found. Productivity statistics at regional level are then compared with the work by Pierani and Rizzi (Pierani and Rizzi, 2009) and by Pierani (Pierani, 2009). They provided agricultural output, input and productivity statistics at regional level using the AGREFIT database (Pierani and Rizzi, 2009) over the period 1951-2002. It can be seen that the relative performances for some regions in 2008-2014 were similar to those provided by Pierani for the last year of his multilateral analysis 2002. However, some stark contrasts were also found. Multilateral comparisons between types of farming show the emergence of the dairy sector, the horticultural sector, the wine and grapes production sector and the fruit production sector as the most productive ones. All types of farming show a declining productive performance except for the wine and grapes production sector. Productivity indexes for size classes of farms show a direct relationship between economic size and performance. Our results show that the composition of regional agricultures in terms of types of farming and in terms of size of farms helps giving a qualitative explanation to the productivity performances observed at regional level. However, this composition does not seem to be the only factor driving their performance. Some other region-specific factors might play an important role in driving their performance and have to be investigated further.

3.2 Literature review

This research aims at providing a picture of the production performance of Italian professional agriculture at an aggregate level, at regional level and along the dimensions of types of farming and class sizes. The more recent available measurements of agricultural productivity in Italy at regional level are provided by Pierani and Rizzi (Pierani and Rizzi, 2009) and by Pierani (Pierani, 2009) and are based on price and quantity statistics collected/derived at the level of Italian regions. To our knowledge, there are no existing comparisons of agricultural productivity in Italy at the level of types of farming and sizes of farms.

The works done by Pierani and Rizzi and by Pierani are based on the data contained in AGREFIT (Pierani and Rizzi, 2009) and cover the period 1951-2002. The first of the two researches provides a description of the AGREFIT database. This is a set of data tables describing, in terms of price and quantity information and at regional level, the evolution of the Italian agriculture from 1951 to 2002. In addition, the authors build chronological chains of bilateral Fisher indexes to describe the evolution of productivity in Italy in the period considered. They find a regional average annual growth rate of productivity larger than 2%. Growth in productivity was particularly robust in the Central and Southern regions with respect to Northern regions due to a greater reduction in the aggregate use of inputs.

However, growth performances were not homogeneous over the period considered. A general slowdown in productivity growth was registered in the period 1977-2002 with respect to the period 1952-1976. The slowdown was particularly marked for regions in the North-East, in the Center and in the South of the country. The authors report also a higher volatility in the growth rates of Southern regions with respect to the rest of the country and claim that such a high level of volatility might due to a higher concentration of crop products in the composition of the aggregate output in the South[1]. Such an output structure could be highly influenced by climatic variability

[1] Aggregate output is composed by 78% of crop products in Southern regions while the share of crop products stands at 55% in the North-Western part of the country.

and the productivity growth trend might be masked by fluctuations due to weather events.

Pierani (Pierani, 2009), using the same dataset, provides multilateral comparisons of output, input and productivity statistics for Italian regions in the same period of time covering 1951-2002. He uses the index number approach to derive aggregate indexes. He provides panel robust indexes of relative TFP levels by using a temporally fixed grid graph in which he uses the Fisher formula to construct bilateral comparisons and the EKS method to construct transitive multilateral comparisons at five-year intervals. Using this method, he shows the impressive growth performance in agricultural TFP in Italy and tests for convergence in productivity levels using panel data unit root tests. He reports the existence of a period of strong regional convergence spanning the years 1960 to 1975 and afterwards, he registers a period long term clustering of Northern and Southern regions along divergent paths up to 2002. The effects of such a development process can be seen in Table 3.1 where some of its results are reported.

With our research paper we aim at providing an updated picture to the productivity statistics provided by Pierani at regional level. By leveraging farm-level heterogeneity we also aim at giving a qualitative explanation of the productivity performances of regions. The hypothesis is that the structure of regional agricultures in terms of types of farming and size of farms influences the aggregate productivity performance at regional level.

3.3 Data

The analysis uses farm-level survey information from the Italian FADN[2]. The sample consists of around 11,000 agricultural holdings for every year of the period 2008-2014. The FADN sampling strategy consists in a stratified random sample plus a constant subsample. The universe is composed of commercial farms[3].

The universe is stratified along the dimension of FADN region[4], types of farming and economic size. To infer total values form the sampled information, each sample is associated with a weight that corresponds to the number of farms that the sampled one represents within their corresponding

[2]Rete di Informazione Contabile Agricola

[3]A commercial farm is defined as a farm which is large enough to provide a main activity for the farmer and a level of income sufficient to support his or her family (FADN website).

[4]FADN regions corresponds to the NUTS2 classification but for Trentino-Alto Adige. In the FADN classification the region is split into regions, Trentino and Alto Adige. The total number of FADN regions is 21.

Region	1951		2002		Average
	Rank	Level	Rank	Level	growth rate
Valle d'Aosta	1	1.661	1	4.446	1.32
Sardegna	2	1.583	9	2.937	0.95
Sicilia	3	1.498	19	2.545	1.15
Puglia	4	1.332	17	2.683	1.56
Calabria	5	1.226	2	3.528	1.60
Emilia Romagna	6	1.197	7	2.992	1.72
Molise	7	1.113	3	3.412	1.90
Lombardia	8	1.086	11	2.992	2.00
Campania	9	1.040	4	3.357	2.07
Piemonte	1	1.000	14	2.706	2.29
Trentino-Alto Adige	11	0.987	12	2.920	2.55
Basilicata	12	0.956	10	2.929	2.17
Veneto	13	0.833	13	2.905	2.39
Lazio	14	0.731	16	2.689	2.63
Friuli Venezia Giulia	15	0.719	6	3.032	2.97
Marche	16	0.715	15	2.699	2.92
Abruzzo	17	0.703	5	3.090	3.03
Liguria	18	0.692	20	2.421	3.15
Toscana	19	0.618	18	2.652	2.98
Umbria	20	0.604	8	2.962	3.35

Table 3.1: Regional level of TFP presented by Pierani (Pierani, 2009)

strata. In the present analysis, productivity statistics are derived at national, regional and at the level of farm typology and farm size using aggregated, weighted farm-level price and quantity information.

The Italian FADN database is composed of 25 detailed tables regarding the structure, activities, balance sheet, and CAP support farms receive. A brief description of the data tables is included in Appendix A. Information contained in these tables is used to derive price and quantity statistics for the creation of aggregate output and input quantity indexes.

Aggregate quantities for any level of analysis is obtained by summing up the weighted farm-level quantities. Prices are obtained as production-weighted average prices. Whenever price information were not available or were incomplete, they were imputed or imported from external data sources.

3.3.1 Output indexes

Output indexes for every level of analysis are created using the information contained in the PRODUCTS table[5] . This table contains information on quantities of the products produced, purchased, transformed, and sold by the sampled farms. Considering the different units of measurement, methods of cultivation[6] and products names, information on a total number of 1047 different products is available in the table.

To get the necessary price and quantity information for the creation of the output indexes several steps are taken. First of all, the production value for each products is imputed from the value information present in the table. Secondly, the products which exhibit extremely large[7] year-to-year percentage change in quantity produced are eliminated from the analysis. These products were excluded because they could have affected aggregate indexes and because their contribution to the final production of the year was very small.

The third and last step, before the use of the index number algorithm, is the selection of products for the creation of the output index. The number of products in the analysis is very large. Excluding the products that exhibited large variations, the PRODUCTS table contains information regarding 1018 products. Such a large number poses two main challenges. First of all it creates computational complexities because of the dimension of the matrices involved in the derivation of the indexes. Secondly, productivity comparisons might be less meaningful by considering such a large variety of products. The

[5]The list of data table of the Italian FADN database is provided in Appendix A

[6]Three methods are included: in open field, in industrial garden and in greenhouse.

[7]The products excluded where those who exhibited a percentage rate of change year after year larger than 10,000%.

reason is because output and input comparisons between units is a function of the common items between the two units. As producing units might have very different composition of their output vector, their output comparisons might be based on a small number of shared products and be less meaningful. It is clear that, two conflicting needs arise in the creation of the indexes:

- the need to use the largest possible number of different products to derive average unit prices that reflect their specific quality;
- the need to aggregate similar products in order to base output and input comparisons on the largest possible value share of total production of the units to be compared.

To reconcile the two needs, a multi-step procedure is taken here. The procedure is based on the idea that the products used in creating the output index should contain all the most detailed information for the most important products in terms of value share. Once these *major products* are identified, the remaining ones are aggregated into macro-categories. Details on the steps undertaken to derive the output index are presented in Appendix C. The output and input indexes for each level of analysis are constructed using a different products aggregation procedure.

3.3.2 Input Indexes

Several inputs have been used in the creation of the aggregate input index. They are: labor, fertilizers, pesticides, external services, water, electricity, seeds, feeding stuff, capital assets, land, reuses, and other general expenses such as commercialization, veterinary services, costs for the transformation of products and others.

Labor input is constructed from the information regarding the salary and hours worked for four groups of workers: family workers, full-time contract workers, temporary contract workers and seasonal workers. The annual salary for family workers is missing and therefore, is imputed by dividing the farms net operating income by the number of family workers.

Information on price and quantity of fertilizers and pesticides is obtained by deflating total costs from the income statement by average prices. Average prices at farm-level for fertilizers and pesticides are obtained by using the information included in the tables FERTILIZERS and PESTICIDES. If farms did not disclose any information in these two tables, their average prices are assigned based on a regional average.

Total costs for seeds and feeding stuff are taken from the INCOME STATEMENT and are deflated using the agricultural price indexes provided by Eurostat[8]. The price indexes are national-level prices and therefore they are equal for every farm.

Total costs for external services are taken from the INCOME STATEMENT of farms and deflated by the number of hours of work by external services. This latter information is included in the table WORK.

Total costs for water usage is taken from the tables CROPS and ANIMAL HUSBANDRY. Volume of water is taken from the table WATER USAGE. The table contains information regarding volume of water usage for a limited number of farms and collected since 2011 only. For this limited set of farms total costs have been deflated by their corresponding water volume to get average prices. For those farms that did not disclose information regarding their water usage, an average price at regional level was imputed and used to derive implicitly their water usage.

Energy is composed of motor fuels and energy for electricity, heating and other uses. Total energy costs for these two components of the energy used were taken from the tables CROPS and ANIMAL HUSBANDRY. Price indexes used were corresponding Eurostat national level price information.

Capital assets considered here includes machines, buildings, plantations and livestock. All categories associated with information regarding their expected life length were included in the analysis. All those categories without expected information on their life-length information have been excluded. Capital services were derived as proportional to the farm-level capital stock while the value component of the capital assets is represented by the sum of the rental prices for all the assets used. Rental prices was constructed as a function of the age of the asset, opportunity cost, depreciation, and expected revaluation.

Land input consists of a quantity component that is represented by the Utilized Agricultural Area (UAA) and a price component which was constructed from the value per hectare included in the table LAND. Land input was considered as non-depreciable asset and its price component was defined as a share of the sales value. The share is represented by the opportunity-cost of the investment.

Farms reuses a portion of their production. It is possible to find the information regarding the quantity and value of reuses in the PRODUCTS table. All products under the heading "Other Uses" were considered as reuses.

The last input considered in the analysis is composed of costs for the commercialization, veterinary services, transformation costs, and costs related to the purchase of consumption materials such as telephone bills, and

[8]http://ec.europa.eu/eurostat/data/database

other means of production. Its value component is represented by the total costs for such expenses while the price component is the Harmonized Index of Consumer Prices (HICP).

A technical section where the major steps for the creation of quantity and prices for each input is presented in Appendix E together with the spanning trees used in chaining bilateral comparisons.

3.4 Productivity measurement methodology

Total Factor Productivity measurements are derived using the Hick-Moorsteen approach. The HM approach defines a TFP index as a ratio of an aggregate output index to an aggregate input index (Coelli et al., 2005; Fried et al, 2008). Aggregate output and input indexes are derived using the index number approach. The index number approach is a non-parametric, non-frontier methodology widely used by statistical agencies for measuring total factor productivity. The index number approach is preferred over the others available because it allows the derivation of productivity measurement with desirable statistical properties and grounded on economic theory without the need to estimate a full technology.

Index numbers use information contained in the value shares of input and output for the aggregation of output and inputs, and allow the comparisons of multi-input multi-output production processes.

The index number formula used in the derivation of the quantity indexes is the Fisher formula. This index is *exact* for a a quadratic production function and is the formula that satisfies most of the tests proposed by Fisher (Fisher, 1922) for the evaluation of index number formulas. However, the Fisher index in its basic fixed-based or chained form, as for all the other index number formulas, fails to satisfy the property of transitivity. In other words, a binary Fisher comparison between two units, s and t, might not be equal to the comparisons of the two units through a third one r.

$$QI_{st} \neq Q_{sr} * QI_{rt}$$

Transitivity is an extremely important property when dealing with cross-sectional or panel comparisons as it ensures the uniqueness of results (Hill, 2004). As the cross-sectional dimension is of the utmost importance in the present research, a TFP measurement methodology that allows the derivation of panel robust comparisons is required.

According to Hill (Hill, 1999; Hill, 2004), transitivity is achieved when using index number formulas for chaining bilateral comparisons across a spanning tree[9].

In this analysis, we adopt the minimum spanning tree approach suggested by Hill where the vertexes of the trees are all the space-time units and the edges are the bilateral Fisher indexes. The spanning tree is selected among all possible ones by finding the one that minimizes the sum of the Paasche-Laspeyres spread of all bilateral comparisons across the tree.

The Paasche-Laspeyres spread is equal to zero when the vector of quantities or the vector of prices between two units is proportional. Thus, by minimizing the sum of the Paasche-Laspeyres spread, the set of bilateral comparisons that have the most similar production structure is found. Thus, output and input comparisons are more meaningful and are less sensitive to the choice of index number formulas. Bilateral comparisons are derived using the Fisher formula and transitive index number are obtained by chaining the set of bilateral comparisons across the tree.

The minimum spanning tree used in the derivation of the output and input indexes at the level of FADN regions, types of farming and size classes are contained in Appendix C and Appendix E.

3.5 Results

Results of the index number measurement methodology are presented in this section. First of all, productivity indexes at country level are presented. Four different TFP indexes at country level are constructed and presented in Table 3.2. The four indexes differ because of the different products aggregation procedure used in the derivation of input and output indexes. Although the aggregation method differs, the final results seem to be robust. Secondly, results at regional level are presented and compared with the statistics from 2002 provided by Pierani (Pierani, 2009). Thirdly, relative TFP levels are presented at the level of types of farming. Ten types of farming are defined in the Italian FADN database and their relative productivity performance is presented here for the different years of the panel. Fourthly, productivity statistics for the three size classes included in the Italian FADN database are shown. Lastly, the composition of regional agricultures is analyzed and compared with productivity performances at regional level. The objective is to have a qualitative inspection of some of the sources of productivity change of regions. Value shares for each type of farming and size classes are associated with the respective regional performance.

[9] A spanning tree is a set of connected vertexes that contains no cycles.

Country level

Relative levels of productivity at country level together with their mean growth rates and their standard deviations are presented in Table 3.2. Four different results are presented, each of them is obtained by using a different products aggregation procedure.

No matter what the products aggregation procedure is, productivity measurements behave similarly. The index is a chained Fisher index normalized to one in 2008. The series exhibit a generally diminishing trend with a productivity peak in 2010. The peak corresponds to the year in which the data collection methodology changed and a period of high turnover rate in the sampled companies as shown in Appendix B. The change in methodology regarded the update of the standard coefficients in the measurement of the Standard Output[10] and the measure by which the economic size of farms was designed. From 2010, farms stopped being classified as commercial based on their standard gross margins[11] and started being classified as such based on their Standard Output.

Year	TFP_{name}	$TFP_{name+um}$	$TFP_{name+um+mc}$	$TFP_{percAgg=90\%}$
2008	1.000	1.000	1.000	1.000
2009	0.898	0.922	0.916	0.983
2010	1.165	1.202	1.171	1.263
2011	0.758	0.783	0.773	0.833
2012	0.722	0.748	0.740	0.795
2013	0.749	0.774	0.765	0.830
2014	0.764	0.772	0.750	0.814
Mean growth	−0.028	−0.022	−0.029	−0.015
Std. growth	0.209	0.209	0.199	0.200

Table 3.2: Chained Fisher TFP indexes for different products aggregation methods, country level

[10] The Standard Output (SO) is the average monetary value of the agricultural output at farm-gate price of each agricultural product (crop or livestock) in a given region. SO of the holding is calculated as the sum of the SO of each agricultural product present in the holding multiplied by the relevant number of hectares or heads of livestock of the holding (FADN website).

[11] The Standard Gross Margin (SGM) is the average value of output minus certain specific costs of each agricultural product (crop or livestock) in a given region. The SGM of the holding is calculated as the sum of the SGM of each agricultural product present in the holding multiplied by the relevant number of hectares or heads of livestock of the holding (FADN website).

Average growth rates were negative for all results. In the case of the raw data, annual average TFP growth rates were ranging between -1.5% and -2.9% depending on the products aggregation procedure adopted.

FADN regions

The FADN classification for Italian regions differ from the Eurostat NUTS2 classification only for one region, Trentino-Adige. Trentino-Alto Adige in the FADN classification is split into two regions Trentino and Alto Adige. The other 19 regions remain unchanged.

Results are normalized in such a way that the relative level of productivity in Piemonte in 2008 was one. TFP relative levels are presented in Table 3.3.

In 2008, the most productive FADN region were Friuli Venezia Giulia followed by Piemonte, Trentino, Lazio and Veneto. Then least productive regions were Liguria, Abruzzo, Molise, Toscana and Sardegna. After seven years, in 2014, the picture has changed remarkably. Emilia Romagna has become the most productive region and has increased its relative performance by around 40%. Friuli Venezia Giulia retained an high ranking position by keeping its productive performance unchanged. An impressive change was registered by Lombardia that from the 11th position jumped up and became the third most productive region in 2014. Lombardia increased its performance by around 40% with respect to its performance in 2008. The regions that have lost positions in the 7-year period are Piemonte, Trentino, Marche, Umbria, Campania, Valle d'Aosta and Liguria.

By taking into account the average relative levels of productivity reported in Table 3.3, there appear to be two clusters of regions associated with a high relative level of productivity. One is located in the North and includes Trentino, Emilia Romagna, Veneto, Lombardia, Friuli Venezia Giulia and Alto Adige, and the other in the South and is composed of Calabria and Basilicata. A cluster with an intermediate average level of productivity is composed of most of the regions located in the Central and Southern part of the country. This group is composed of Umbria, Lazio, Marche and Toscana together with Puglia, Sicilia, Campania and Molise. Also Piemonte is part of this group. This group has on average 25% less productivity than the first group. The last cluster is composed of Sardegna, Abruzzo, Valle d'Aosta and Liguria. On average, they have around 50% of the productivity of the first group.

By comparing the ranking of regions based on their average relative levels of productivity with the productivity ranking provided by Pierani (Pierani, 2009) few features emerge. First of all, there is a group of regions that have their position almost unchanged since 2002. This group is composed

FADN	2008		2014		Average		Median	Average
Region	Rank	Level	Rank	Level	Rank	Level	growth	growth
FV	1	1.139	2	1.129	6	0.774	-0.063	+0.139
PI	2	1.000	7	0.818	14	0.567	-0.041	+0.101
TR	3	0.991	9	0.722	2	0.882	-0.054	+0.103
LA	4	0.983	5	0.990	10	0.661	-0.098	+0.215
VE	5	0.901	4	1.026	4	0.811	+0.076	+0.133
BA	6	0.873	6	0.899	8	0.703	+0.064	+0.099
MA	7	0.830	10	0.698	16	0.549	+0.082	+0.028
CL	8	0.803	8	0.805	1	0.908	+0.035	+0.092
ER	9	0.801	1	1.378	3	0.853	+0.086	+0.155
UM	10	0.788	12	0.599	9	0.680	-0.086	+0.054
LO	11	0.772	3	1.090	5	0.797	+0.317	+0.183
CM	12	0.728	18	0.412	13	0.625	-0.135	+0.095
AA	13	0.583	14	0.546	7	0.708	-0.064	+0.067
SI	14	0.561	15	0.515	12	0.654	-0.049	+0.092
VA	15	0.520	20	0.352	20	0.476	+0.025	-0.016
PU	16	0.518	11	0.674	11	0.661	+0.041	+0.057
LI	17	0.514	21	0.289	21	0.404	-0.047	-0.075
AB	18	0.495	17	0.474	19	0.486	+0.097	+0.074
MO	19	0.477	19	0.360	15	0.566	-0.021	+0.020
TO	20	0.424	13	0.575	17	0.528	-0.019	+0.145
SA	21	0.337	16	0.478	18	0.496	+0.025	$^+$0.115

Table 3.3: Ranking and relative levels of TFP, FADN regions

of Calabria, Basilicata, Umbria, Friuli Venezia Giulia, Piemonte, Marche, Toscana and Liguria.

Secondly, a group of regions have a significantly different positions with respect of the results in Pierani. Following Pierani, Trentino - that was a regions with a medium level of relative productivity in 2002 - is one of the leading regions in terms of productivity according to this research. Emilia Romagna have climbed up few positions with respect to 2002 while Veneto have increased remarkably its position together with Puglia. Two regions that have lost a large number of positions are Campania and Molise. They were respectively the fourth and the third in terms of relative productivity levels in 2002 and they are now, on average, the thirteenth and the fifteenth of the group. Other regions that have seen a considerable positive relative change from 2002 are Lombardia, Alto Adige, Lazio and Sicilia. Sardegna have lost several positions instead.

The third feature that emerges is that there are two regions that have changed dramatically their position in terms of relative levels of productivity. These two are Valle d'Aosta and Abruzzo. In the work of Pierani, Valle d'Aosta was the first region in terms of productivity levels either in 1951 and in 2002. In the statistics presented here instead, Valle d'Aosta is almost at the bottom of the ranking. According to the analysis by Pierani, Abruzzo was ranking fifth in 2002 and is now ranking 19th.

Time-series of productivity indexes together with their HP-smoothed series and their average are presented in Appendix G. The smoothing parameter of the Hodrick-Prescott filter is equal to 0.5. The smoothing helps identifying the productivity trend in a possibly noisy time-series. TFP estimates capture the effects of factors such as changes in climate conditions and natural resources and these effects might mask productivity trends (Fuglie et al., 2016).

Types of farming

In this section, the results of TFP measurements for the different types of farming included in the Italian FADN database are presented. There are ten types of farming practices considered here. They are defined by the Italian FADN as the type of crop or livestock product for which the Standard Output contribution to the total Standard Output at farm-level is maximum. The link between the detailed types of farming at the EU level and the types considered by the Italian FADN is provided in Appendix F.

The types of farming considered here are Dairy, Cereals, Grazing livestock, Fruits, Granivores, Mixed, Olives, Horticulture, Arable crops and Wine. Productivity indexes are normalized in such a way that productivity for Mixed farms in 2008 is equal to one.

TF	2008		2014		Average		Average
	Rank	Level	Rank	Level	Rank	Level	growth
Dairy	1	1.856	2	1.446	1	1.581	-0.036
Horticulture	2	1.687	3	1.339	2	1.446	-0.036
Fruits	3	1.485	6	1.149	4	1.351	-0.040
Arable crops	4	1.331	5	1.158	6	1.138	-0.012
Olives	5	1.330	4	1.263	5	1.305	-0.007
Wine	6	1.286	1	1.471	3	1.410	+0.023
Mixed	7	1.000	8	0.801	8	0.927	-0.030
Cereals	8	0.951	7	1.025	9	0.926	+0.024
Grazing liv.	9	0.748	9	0.713	10	0.692	+0.007
Granivores	10	0.651	10	0.449	7	1.050	+0.205

Table 3.4: Ranking and relative levels of TFP, types of farming

In 2008, the most productive sectors are the dairy sector, the horticultural sector and the production of fruits. The dairy sector was almost three times as productive as the least productive sector, i.e., the granivores sector. In 2014, the ranking has not changed dramatically. The only remarkable change was made by the wine and grapes production sector that, with an average annual growth rate of +2.3%, moved from the sixth position to the first in seven years. The Wine sector has increased its productive performance by around 12% in the period considered. The relative position of the other types of farming remained almost unaltered even though most of them have exhibited negative average annual growth rates over the period.

By taking a look at the ranking of the average relative level of TFP by types of farming, it is clear that the farming type that is most productive is the dairy sector. This sector is followed by the horticultural and wine sectors both with a level of productivity that is around 90% of that of the dairy sector. The wine sector is followed by the fruits production and by the olives and olive oil production sectors. These two latter sectors have, on average, respectively 85% and 82% of the productivity level of the dairy sector. Arable crops and granivores farming follow. Mixed farms and cereals have similar average relative productivity levels that is, on average, around 60% of the productivity of the dairy sector. The least productive sector is represented by the Grazing livestock sector. It has a considerably low productivity level around 43% the level of the dairy sector.

The time-series of relative productivity indexes, the HP-smoothed productivity indexes and their average levels are presented in Appendix H.

Size classes

In this subsection, indexes at the level of size classes of farms are derived. The size classification used is provided by the Italian FADN. It is based on the concept of economic size and Standard Output, and differs from the other classification provided at European level. It is composed of three classes: large, medium-sized and small farms. A small farm is a farm with a Standard Output lower than 25,000 EUR, a medium-sized farm has a Standard Output larger than 25,000 EUR and lower than 100,000 EUR, while large farms have a SO larger or equal to 100,000 EUR.

This classification is preferred over the others available because it is the only one that does not change throughout the period 2008-2014. However, because the calculation of the unit value of the Standard Output for each product changed between 2008-2009 and 2010-2014, the original FADN classification has been modified in this analysis in order to have a relatively constant composition across classes. In particular, the Unit Standard Output Coefficients of the period 2010-2014 were used to compute the economic size of farms for all time periods togheter with the thresholds defined earlier. A detailed description of the issues and of the procedure used is provided in Appendix G.

Statistics on productivity levels for each size class in 2008 and in 2014 together with their average level throughout the period 2008-2014 are presented in Table 3.5. All statistics are relative to productivity level of Medium-sized farms in 2008. As it is possible to see, there exists a direct relationship between economic size and productivity and this relationship remained stable over time. Large farms were the most productive in 2008 and remained the most productive in 2014. The ranking of the medium-sized farms and small farms remained unchanged.

Size	2008		2014		Average		Average
classes	Rank	Level	Rank	Level	Rank	Level	growth
Large	1	2.054	1	1.381	1	1.581	-0.060
Medium	2	1.000	2	0.866	2	0.893	-0.021
Small	3	0.630	3	0.535	3	0.572	-0.024

Table 3.5: Ranking and relative levels of TFP, size clases

On average, large farms are almost three times as productive as small farms and close to be two times more productive than medium-sized farms. However, productivity performances for the three size classes seem to change considerably over time and the productivity gap of size classes seems to narrow. Average annual growth rates of TFP were negative for all class sizes but with different magnitude. While medium-sized and small farms have an average annual growth rate ranging between -2.4% and -2.1%, large farms experienced an average annual growth rate of -6.0%.

Structure of regional agricultures

In this section, the composition of regional agricultures in terms of types of farming and size of farms is inspected. The hypothesis to be tested here is that the agricultural structure of regions is what drives their performance. In Table 3.6, Table 3.7 and Table 3.8 the average annual shares of total production coming from the different types of farming and for the different size classes within each region are presented. The regions presented in Table 3.6 are the ones at the top of the average productivity ranking for the period 2008-2014.

TF	AA	BA	CL	ER	FV	LO	TR	VE
Dairy	0.318	0.061	0.014	0.280	0.164	0.495	0.155	0.155
Cereals	0.000	0.202	0.019	0.065	0.143	0.150	0.006	0.120
Grazing liv.	0.019	0.107	0.033	0.020	0.018	0.038	0.028	0.024
Fruits	0.434	0.204	0.268	0.167	0.066	0.025	0.451	0.063
Granivores	0.003	0.002	0.000	0.039	0.031	0.054	0.000	0.022
Mixed	0.030	0.078	0.073	0.075	0.082	0.033	0.044	0.076
Olives	0.000	0.039	0.467	0.000	0.000	0.000	0.000	0.001
Horticulture	0.103	0.150	0.039	0.134	0.131	0.125	0.062	0.181
Arable crops	0.014	0.122	0.051	0.163	0.038	0.050	0.048	0.092
Wine	0.079	0.034	0.038	0.057	0.327	0.029	0.210	0.266
Size	AA	BA	CL	ER	FV	LO	TR	VE
Large	0.141	0.308	0.200	0.710	0.628	0.780	0.247	0.596
Medium	0.679	0.377	0.297	0.211	0.230	0.153	0.497	0.276
Small	0.179	0.315	0.503	0.079	0.143	0.067	0.256	0.128

Table 3.6: Average share of production value by source, group 1

In terms of types of farming, some regions are highly specialized with an average annual share of one of their specialization larger than 40%. These regions are Alto Adige, Calabria, Lombardia and Trentino. They are highly specialized in fruits, wine and olives production and in the dairy sector. Basilicata, Emilia Romagna, Friuli Venezia Giulia and Veneto have a more diversified agricultural production structure. Basilicata has, on average, five types of farming each with an annual share larger than 10%. Emilia Romagna, Friuli Venezia Giulia and Veneto have four types of farming with an average annual share on the total production value larger than 10%. For what regards the size of farms, a clear feature seems to emerge in this group of regions. The regions in the Center-North such as Alto Adige, Emilia Romagna, Friuli Venezia Giulia, Lombardia, Trentino and Veneto are all characterized by a large share of production coming from large and medium-sized farms while regions in the South, e.g., Basilicata and Calabria have a large share of their production that is produced by small farms. In particular, more than 50% of the production value produced in Calabria is coming from small farms. On the opposite side, in Emilia Romagna, and Lombardia large farms produce more than 70% of the regional production value. Such concentration of activities might influence the relative levels of productivity of these regions. In particular, the high level of relative productivity of the regions located in the North might be easily associated with the concentration of activities into large farms and in the specialization into highly productive sectors such as the dairy sector, the wine and the fruits production sectors. More difficult is to explain the remarkable performance of Basilicata and Calabria. Their production structure is largely made of small and medium-sized farms that are specialized into types of farming that are not associated with the highest levels of productivity such as the production of cereals and olives.

The second group of regions is associated with an medium level of relative productivity that is comprised between 0.7 and 0.5. These regions are Campania, Lazio, Marche, Molise, Piemonte, Puglia, Sicilia, Toscana and Umbria. In Table 3.7 their average annual share of production value by type of farming and size of farms is presented.

What is apparent from the table is that, in general, these regions seem not to be concentrated into few activities but rather they produce a large variety of products. The dairy sector is particularly relevant in Campania, Lazio, Molise and Piemonte. Horticulture is one of the major type of farming in these regions with an average annual production value exceeding 20% of their total production for Campania, Lazio, Sicilia and Toscana. Other major specializations for these regions are the production of fruits and the production of wine. In terms of size of farms, Piemonte share the typical production structure of Northern regions with a large portion of its production coming from large farms and a small portion coming from small farms. Also Toscana shares a similar structure with an average annual share of production value coming from large and medium-sized farms exceeding 80%. All the other regions in this group have a smaller share of production value coming from large and medium-sized farms.

TF	CM	LA	MA	MO	PI	PU	SI	TO	UM
Dairy	0.177	0.165	0.010	0.171	0.148	0.069	0.038	0.012	0.044
Cereals	0.020	0.038	0.241	0.243	0.179	0.081	0.043	0.058	0.156
Grazing liv.	0.033	0.089	0.057	0.092	0.083	0.025	0.069	0.031	0.069
Fruits	0.165	0.174	0.050	0.049	0.104	0.149	0.221	0.139	0.054
Granivores	0.015	0.008	0.033	0.023	0.117	0.000	0.006	0.005	0.044
Mixed	0.048	0.045	0.095	0.147	0.068	0.065	0.053	0.054	0.136
Olives	0.066	0.060	0.018	0.016	0.000	0.138	0.051	0.043	0.102
Horticulture	0.314	0.251	0.164	0.055	0.042	0.202	0.288	0.242	0.064
Arable crops	0.119	0.120	0.222	0.130	0.055	0.088	0.091	0.080	0.202
Wine	0.043	0.050	0.111	0.073	0.204	0.182	0.140	0.337	0.131
Size	CM	LA	MA	MO	PI	PU	SI	TO	UM
Large	0.435	0.433	0.365	0.221	0.608	0.297	0.401	0.572	0.456
Medium	0.264	0.304	0.331	0.387	0.270	0.335	0.352	0.241	0.274
Small	0.302	0.263	0.304	0.392	0.122	0.367	0.247	0.187	0.270

Table 3.7: Average share of production value by source, group 2

While for most of the regions in this group seems reasonable to assume that their production structure - with a diversified structure and a large share of small farms - might influence their average production, it seems more difficult to explain the 14th and 17th position in the productivity ranking for Piemonte and Toscana. They have a production structure largely composed of large and medium-sized farms and they have their activities concentrated into highly productive sectors such as the Dairy sector, the Fruit and Wine production and Horticulture.

In Table 3.8 the composition of the remaining group of regions is presented. These are the least productive regions during the period 2008-2014 and they have an average relative level of productivity below 0.5.

The first feature that emerges is that Liguria, Sardegna and Valle d'Aosta have their activities concentrated into a single type of farming. Liguria has on average more than 65% of its aggregate production value coming from Horticulture. Valle d'Aosta has more than 60% of its annual production value coming from the dairy sector while Sardegna has an average annual share of production value coming from the farming of grazing livestock higher than 43%. Sardegna has a large share of its production coming from other sectors such as horticulture and the dairy sector. Valle d'Aosta has large annual share coming from grazing livestock. Abruzzo has a more diversified structure with a 25.5% of its average production value coming from the production of grapes and wine, a 19.9% coming from horticulture and almost

TF	AB	LI	SA	VA
Dairy	0.084	0.017	0.110	0.602
Cereals	0.040	0.002	0.022	0.000
Grazing liv.	0.072	0.040	0.437	0.194
Fruits	0.066	0.064	0.036	0.051
Granivores	0.010	0.002	0.013	0.000
Mixed	0.085	0.023	0.062	0.037
Olives	0.030	0.102	0.015	0.000
Horticulture	0.199	0.657	0.153	0.065
Arable crops	0.159	0.040	0.085	0.014
Wine	0.255	0.054	0.067	0.094
Size	**AB**	**LI**	**SA**	**VA**
Large	0.365	0.311	0.447	0.308
Medium	0.379	0.365	0.376	0.426
Small	0.257	0.324	0.178	0.266

Table 3.8: Average share of production value by source, group 3

16% coming from growing arable crops. In terms of size of farms, Sardegna is the region with an higher average annual share of production value coming from large farms. The remaining three regions have most of their production coming from medium-sized farms and a large share coming from small farms. Except for Sardegna that is specialized in the Grazing livestock, all regions are specialized into sectors of medium and high average level of productivity. Nevertheless, their relative performance is relatively poor. In terms of size of farms, the only region with a production structure characterized mostly by large farms is Sardegna and yet its productive performance is low.

A quantitative look at the associations between productivity, and types of farming and size classes is given in Table 3.9. Here, the correlations between relative levels of TFP in each of the year for each region and their corresponding share of production value for each type of farming and each size class are presented.

From the correlation coefficient, it seems as if specializing into some types of farming is associated to a higher level of productivity. A higher share of production value coming from the dairy sector, the fruit production sector, and the olives production sectors is associated with higher levels of relative productivity. Sometimes, as in the case of the fruit production and olives production sector, the correlation coefficient is highly significant. For the dairy sector instead, the linear association seems not to be statistically sig-

TF	Corr. coef.
Arable crops	-0.009
Cereals	0.018
Dairy	0.137^{*}
Fruits	0.245^{***}
Granivores	-0.037
Grazing liv.	-0.264^{**}
Horticulture	-0.267^{**}
Mixed	-0.028
Olives	0.382^{***}
Wine	-0.035
Size	**Corr. coef.**
Large	0.033
Medium	-0.012
Small	-0.039

Table 3.9: Correlation between performance and sectoral composition by source. $^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$.

nificant. In terms of class sizes, a higher share of large farms is associated with a higher level of relative productivity. However, the relation seems not to be clear as all correlation coefficients are not statistically significant. A negative linear relation exists between productivity and the concentration of medium-sized or small farms.

All in all, a relationship between the composition of regional agricultures and their productivity performance seems to exist but it is not clear cut. A positive relation seem to exist between the specialization into some agricultural sectors such as the Dairy sector, the Olives production sector and the Fruit production sector. Also, there seems to exist a positive relation between size of farms and productivity levels. Yet, these associations are not so clear. A deeper inspection into the sources of the productivity performance at regional level would be required before coming to conclusions. Such an inspection has to take into account the composition of the regional agricultures in terms of types of farming and class sizes.

3.6 Conclusions

Agricultural productivity in Italy exhibits negative annual growth rates at country level during the period 2008-2014. Using different methods for the construction of the output index, this work shows that relative levels of productivity in Italy decreased by around 20% in the period.

This decreasing trend is also observed at sub-national level. Multilateral productivity comparisons are created for types of farming and for classes of farm size and they both show a generally decreasing trend.

For what regards productivity by types of farming, the most productive specializations are the Dairy sector, the Horticultural sector, the fruits production sector and the wine production sector. The least productive sectors are the granivores sector, the mixed sector, the cereals production sector and the Grazing livestock sector. This latter types of farming has, on average, a relative level of productivity that is around 44% of that of the Dairy sector. Relative levels of productivity of all sectors follow a downward trend with the exception of the Wine sector that shows an increasing trend over time.

In terms of farms size, there is a positive relation between TFP and size of farms. On average, large farms are almost three times as productive as small farms and more than 40% more productive than medium-sized farms. Growth rates of relative productivity levels by size classes are all negative with large farms showing the fastest decrease in productive performance over time. Medium-sized farms and small farms exhibit an average annual growth rate of respectively -2.1% and -2.4%.

The agricultural sector within FAND regions has a composite structure with production coming from different types of farming and farms of different size. The resulting productive performance of regions over time is mixed. However, there are large disparities in TFP relative levels. Three groups can be identified with respect of their average relative productive performance in the period. Regions with a higher average relative levels of productivity are Alto Adige, Basilicata, Calabria, Emilia Romagna, Friuli Venezia Giulia, Lombardia, Trentino and Veneto. The group of regions with the lowest average relative levels of productivity are Abruzzo, Liguria, Sardegna and Valle d'Aosta. The remaining group has an intermediate average relative levels of productivity and includes most of the central regions such as Lazio, Marche, Toscana and Umbria together with regions from the South such as Campania, Molise, Puglia and Sicilia. Piemonte is the only regions located in the Northern part of the country that also belongs to this group.

There seems to be a relation between relative levels of TFP for FADN regions and their composition in terms of types of farming and size of farms. In particular, a higher presence of the dairy sector, the fruits production sector and the Olives production sector seems to be associated with higher levels of productivity. A higher incidence of the horticultural and grazing livestock sectors in the whole agricultural production process of regions seems to be associated with lower levels of relative TFP instead. Size of farms matters in the sense that the presence of large farms seems to be associated with higher levels of productivity but the relation is not found to be statistically significant.

Chapter 4

Spillover effects and diffusion process of agricultural productivity in Italy

4.1 Introduction

Understanding the diffusion process of agricultural productivity is useful for investment decisions at different policy levels. R&D investments and on-farm innovation are considered to be the main drivers of agricultural productivity growth (Fuglie et al., 2016). Policy making at regional, national and international level can channel resources into specific instruments to promote the introduction of innovation into the sector and to drive up productivity. Then, through inter-regional and inter-sectoral channels innovation diffuses in space and over time leading to positive externalities in the agricultural production process of inter-related producing units.

This paper aims at modeling the diffusion process of productivity shocks in specific geographical locations within the Italian agriculture. This can provide useful insights for guiding R&D investments into the sector.

Diffusion effects of productivity are modeled by estimating the degree of spatial and temporal dependence of agricultural TFP levels across Italian NUTS3 and by assuming a unitary productivity shock hitting specific locations.

Multilateral Total Factor Productivity measurements are derived at NUTS3 level over the period 2008-2014 using the index number approach. A TFP index is represented by a ratio of an aggregate output quantity index to an aggregate input quantity index. Comparability of measurements in space and time is achieved by chaining bilateral comparisons across a minimum spanning tree as suggested by Hill (Hill, 1999; Hill, 2004). Vertexes of the spanning tree are represented by all space-time units while edges are bilateral Fisher comparisons. Productivity statistics at NUTS3 level are obtained by aggregating weighted farm-level statistics provided by the Italian FADN.

The inspection of the degree of space-time dependence starts with some exploratory analyses. A set of spatial autocorrelation tests are carried out in each year of the panel using different assumptions regarding the spatial correlation structure across NUTS3. Results show a limited degree of spatial autocorrelation. Productivity clustering is found in five years of the panel and its maximum extent was found for relatively narrow spatial correlation structures. A visual inspection helps uncovering productivity clustering in the Northern part of the country, across the Padan plain, and in the Southern part across Puglia, Basilicata, Campania, Calabria and Sicilia.

Space-time dependence of TFP is used in modeling the diffusion process and is obtained by estimating a space-time linear panel data model. A linear relation between relative levels of productivity of NUTS3 and their temporal and spatial lag is assumed. Some additional explanatory variables are included in the specification. The selected adjacency matrix is a row-standardized distance matrix in which neighbors are identified as the set of NUTS3 whose centroids falls within a 50 kilometers radius from the centroid of each corresponding NUTS3. This spatial correlation structure has been selected out of a series of alternatives based on the maximum value of the maximized log-likelihood and assuming stationarity in space and time. The relation is estimated using the BCLSDV estimator. Elhorst (Elhorst, 2010) has shown that the BCLSDV estimator outperforms, in terms of bias and mean square error, other available estimation methodologies.

Then, using the estimated model and assuming a unitary shock occurring in specific spatial units, the spread of productivity is observed across NUTS3 over time.

By focusing on one the most diffusive region in Italy, Emilia Romagna, it is shown that the degree of productivity diffusion in Italy is limited. A unitary shock hitting every NUTS3 in Emilia Romagna drives up productivity levels of other locations, even far from the epicenter of the shock. Cumulating the effect of the shock in every time period, it is possible to derive the spillover for every NUTS3 in all time periods. Due to narrow correlation structure and the limited degree of temporal dependence, the long-run spillover effect varies remarkably in time and space across provinces. NUTS3 that are closer to the epicenter of the productivity shock have a total spillover effect higher than those further away. For these regions, spillover effects are quiet rapid and reach their maximum level after few time periods. Approximately, a unitary shock hitting NUTS3 in Emilia Romagna reach their maximum effects in the NUTS3 in Lombardia in 4/5 years. For NUTS3 that are far away from the source of the shock, these spillover effects are lower and take more time to spread. The spillover effect of a unitary shock in Emilia Romagna takes around 8 years to reach their peak in NUTS3 in Abruzzo.

4.2 Literature review

Since the development of the endogenous growth theory, an extensive strand of literature has been focusing on the relationship between R&D investments, innovation spillover effects, and TFP growth in agriculture.

A general result points to the existence of a positive relationship between R&D effort, innovation and TFP growth (Johnson and Evenson, 1999; Craig et al, 1997; Alfranca and Huffman, 1999; Shimmelpfenning and Thirtle, 1999; Gutierrez and Gutierrez, 2003; Esposti, 2011; Lin and Kwan, 2013; Fuglie et al., 2016). One of the main contribution of R&D activities to agricultural productivity is transmitted in the form inter-sectoral and inter-regional spillover (Alfranca and Huffman, 1999; Johnson and Evenson, 1999).

Due to proximity and trade, TFP levels in agriculture should converge across countries and regions within and across countries due to the diffusion process of technology. However, empirical evidence points to large cross-country productivity differentials (Ball et al. , 2010; Sheng et al. 2014). Large differentials are also found across regions within the same country (Pierani, 2009; Hayami and Ruttan, 1969; Maietta et al. 1995). These productivity differentials were attributed to differential diffusion processes of innovation due to local specificities (Griliches, 1960; Nelson 1969; Hayami and Ruttan, 1969).

Acemoglu and Zilibotti (Acemoglu and Zilibotti, 2001) have argued that productivity differentials can be explained by the fact that innovations are developed in specific economic environment, 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.

Griliches (Griliches, 1960) have recognized that the pattern of diffusion of innovations, such as hybrid corn, has been characterized by marked geographic differences because of location-specific economic factors.

In agriculture production processes are highly influenced by location-specific factors such as topography, land quality and climate (Esposti, 2011; Griliches, 1960). These specificities might influence the agricultural production processes across locations and steer the process of diffusion of technology leading to wide productivity differentials.

Hayami and Ruttan (Hayami and Ruttan, 1969) have argued that due to the differential diffusion of agricultural technology, and, to an even greater degree, of differential diffusion of the scientific and technical capacity to invent and develop new mechanical, biological and chemical technology specifically adapted to the factor endowments and prices in a particular country or region, agricultural producers are not all on the same micro-production function.

It is quite intuitive to think that the spread of positive externalities takes place across producing units over a certain length of time. Imitation and adoption might be lengthy processes that influence the speed at which technology can spread. Contemporaneous effects cannot be not ruled out, but lagged effects might play an important role in the diffusion process of innovation.

Empirical analyses aimed at explaining spillover effects have provided measures of correlation between productivity measures and R&D efforts mostly focusing on static models (Johnson and Evenson, 1999) or in spatially lagged frameworks (Keller, 1999; Abreu and Forax, 2004), or providing summary statistics on the space time evolution of output, input and productivity measures (Griliches, 1960; Acquaye et al. 2010). To our knowledge, the only studies that take into account both spatial and temporal dimensions in examining the dynamics of productivity are Esposti (Esposti, 2011), and Lin and Kwan (Lin and Kwan, 2013).

Research focused on the quantitative analysis of diffusion processes is recent. Examples of this literature outside the agricultural sector are those from Parent and LeSage (Parent and LeSage, 2010) and Debarsy et al. (Debarsy et al. 2012). The first of these two works focuses on the spreading of the positive effects, in terms of commuting time, to highway segments following investments for the improvement of a single segment. In the second research, the authors inspect the bootlegging effect of cigarettes buyers across neighboring US states.

For what regards the measurement of agricultural productivity in Italy, there are several works that were aimed at measuring productivity levels and rate of growth in Italian provinces and regions. The latest contributions are given by Maietta and Viganò (Maietta and Viganò, 1995), Pierani and Rizzi (Pierani and Rizzi, 2009), Pierani (Pierani, 2009) and Esposti (Esposti, 2011). These studies have focused the attention on the measurement of productivity levels and growth rates, and/or on testing convergence hypotheses of productivity levels and of growth rates of productivity. However, none of them have specifically focused on the diffusion of productivity across locations over time in Italy.

Maietta and Viganò, estimating a stochastic frontier, identified efficiency levels and technical change for the Italian agriculture using statistics at

NUTS3 level. They studied the evolution of these productivity parameters through 1980-1990. They identified an outward shift of the frontier due to technical change, and by assuming a time-varying efficiency component for the NUTS3, have found a downward trend in the general level of efficiency in Italy.

Comparisons of levels and growth rates of TFP at a subnational level in Italy was carried out by Pierani, and Esposti. Pierani, studying multilateral indexes of relative productivity throughout the period 1951-2002 at regional level, have found evidences of TFP convergence in levels of TFP only through the period of time spanning 1967-1972. In the subsequent period under study, he found productivity clustering along divergent development paths.

Using the same dataset[1] Esposti (Esposti, 2011) has studied whether and why productivity growth rates tend to equalize in the long-run. Using panel data unit root tests, he found evidence of convergence in growth rate only for a limited number of regions. He argues that, due to the counter-balancing of convergence and divergence forces, TFP growth of regions did not diverge. He also estimated the relationship between TFP growth and public investments in R&D . He found a strong positive relation between R&D investments and TFP growth rates.

The aim of this chapter is to extend the literature on agricultural productivity measurement and to combine it with the literature on spillover effects and diffusion processes. It does so by providing a model for the diffusion process of TFP across Italy, at high spatial resolution, and to quantify spillover effects due to productivity shocks. The evidence put forward by this work could be used to explain observed disparities in productivity levels and growth rates, and can be used to guide R&D investment decisions.

4.3 Data

The data used for the analysis consist of observations on total factor productivity measurements in the panel of 107[2] Italian NUTS3 observed during the period 2008-2014.

Productivity measurements are derived using the Hicks-Moorsteen, i.e., by a ratio of an output quantity index to an input quantity index (Fried et al., 2008; Coelli et al., 2005). Indexes are derived using the index number

[1] AGREFIT (Pierani and Rizzi, 2009)

[2] The number of NUTS3 according to Eurostat classification corresponds to the administrative division of Italian provinces as of 2011. In the present research, three provinces were merged together with neighboring ones in order to derive detailed accounts on input and output indexes for every spatial unit.

approach and the Fisher formula.

The Fisher index posses a number of interesting statistical properties but fails to satisfy the property of transitivity., i.e., a comparison between two units might not be equal to the comparisons of the two units through a third one. Transitivity is a very important property for cross-sectional and panel comparisons. In the present analysis, productivity statistics comparable across units and over time are derived using the minimum spanning tree method proposed by Hill (Hill, 1999; Hill, 2004). Transitive indexes are 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 sum of the Paasche-Laspeyres spreads between each bilateral comparisons.

Price and quantity statistics used for the derivation of the indexes are aggregation of weighted price and quantity statistics at farm-level as provided by the Italian FADN[3]. The sample consists of around 11,000 commercial farms[4] sampled annually with a stratified random sampling strategy and contains also a constant sample. A weight is attached to each sampled farm in order to reflect the number of farms that the sampled one represents in the universe of commercial farms in Italy.

Productivity statistics at NUTS3 level are presented in Figure 4.1. The data show a low degree of productivity clustering. Clusters are highly localized. By visual inspection, NUTS3 clusters in small groups of relatively homogeneous productivity levels. High levels of productivity are observed in the Northern part of the country especially across the Padan Plain. High levels of productivity are also found in clusters in the Southern part of the country especially in Campania, Puglia, Calabria and Sicilia. The Center is mostly characterized by low levels of productivity instead.

The distribution for the TFP index and its logarithm are found in Figure 4.2. While the Jarque-Bera test strongly rejects the hypothesis of normality of both empirical distributions, the distribution of the log-transformed data show a higher degree of symmetry.

The observation that productivity groups into clusters of similar levels can be tested using the Moran test. In few words, the Moran test inspects the magnitude and statistical significance of a linear relationship between productivity levels for each NUTS3 and the average productivity level of their neighbors. While a positive statistically significant linear relation between these two variables identifies productivity clustering, a negative relation im-

[3]Farm Accountancy Data Network

[4]A commercial farm is a farm that is large enough to provide a main source of income for the farmer and its family

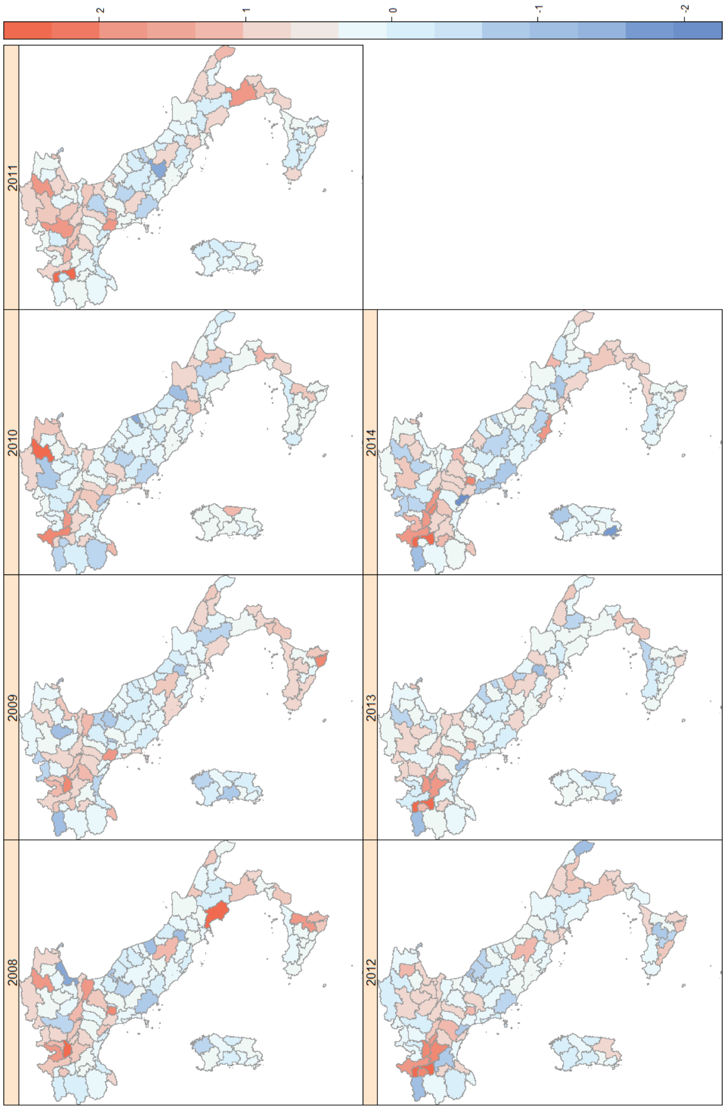

Figure 4.1: Relative productivity levels (in logs) for Italian NUTS3

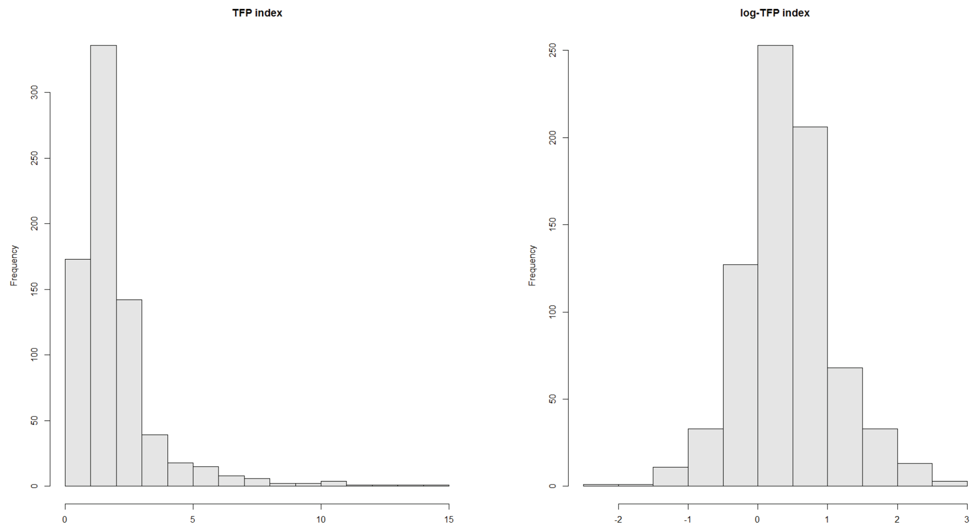

Figure 4.2: Empirical distribution of TFP and log-TFP

plies that high levels of productivity are surrounded by areas with low levels of productivity and vice versa.

As the distribution of the logarithm of the productivity index is statistically closer to a normal distribution, we decided to present the set of Moran tests using the logarithm of the productivity relative levels as target variable in each of the accounting years of the panel.

A series of spatial correlation tests was carried out iteratively using, for each year of the panel, different assumptions regarding the correlation structure across observations. The binary correlation structure used was always a function of the radial distance between centroids. At each iteration, the definition of neighborhood changed according to the length of the radius considered. We tried the set of radius lengths comprised in the interval [35 km, 500 km] using a step of 5 km at each iteration.

Results of the tests are presented in Figure 4.3. Significant Moran I statistics are found in 2008, 2009, 2011, 2012 and 2014. In all these cases, the Moran I statistic is positive pointing to productivity clustering. For 2010 and 2013, the spatial autocorrelation tests failed to reject the null hypothesis of no spatial autocorrelation considering any of the assumptions regarding the correlation structure. The highest and statistically significant, at 95% confidence level, Moran I statistics are found for different definitions of neighborhood in each of the years considered. In 2008, the highest statistically significant Moran I statistics was found considering a radial distance of 55 km, in 2009 a distance of 50 km, in 2011 a distance of 100 km, in 2012 of

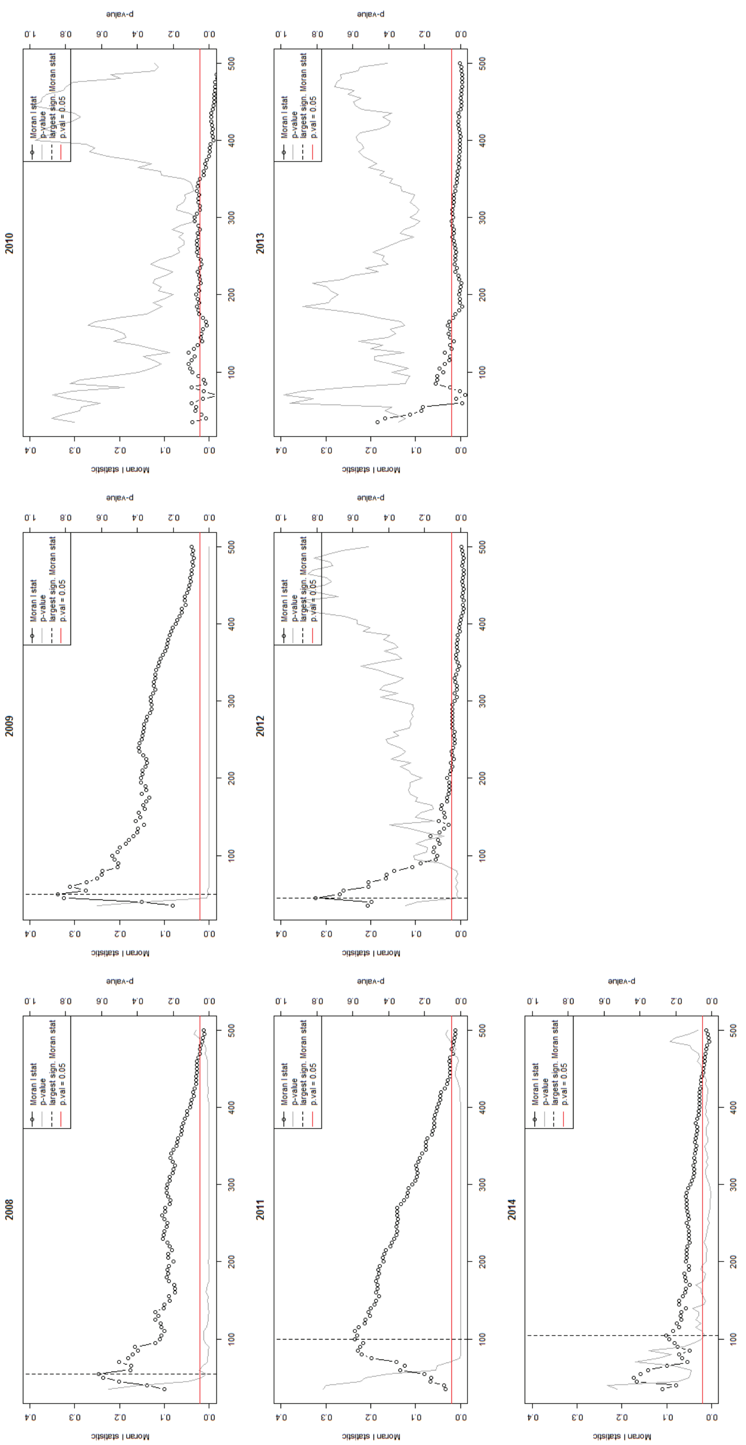

Figure 4.3: Moran tests using different spatial weight matrices for every time period

45 km and in 2014 up to 105. In all the time periods in which productivity clustering was statistically significant, the highest Moran I statistics was ranging between 0.1 and 0.35. All these evidences point to a limited degree of productivity clustering across NUTS3 in Italy.

To quantify the degree of spatial and temporal dependence of productivity across NUTS3 a dynamic spatial model is estimated. This model is estimated using information regarding relative TFP levels of NUTS3 and a set of exogenous variables. The exogenous variables are included in the model to capture potential sources of temporal and spatial variability that might TFP at NUTS3 level. These exogenous variables included are: the year-to-year turnover rate of the sampled farms for each NUTS3, the estimated percentage deviation of estimated rainfall level from a long-time trend, the number of Utilized Agricultural Area (UAA) in logarithm, the share of UAA located in plain areas, the average CAP support per beneficiary (Sotte and Baldoni, 2016)[5], the share of UAA of large farms, the share of UAA of small farms, the share of UAA belonging to farms specialized in Grazing Livestock and the average altitude of the UAA (included as a quadratic polynomial).

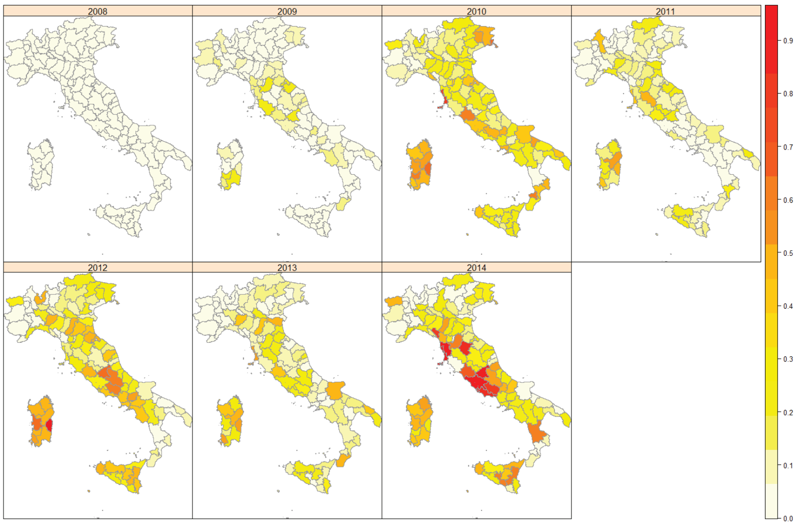

Figure 4.4: Year to year turnover rate by NUTS3

Data on the year-to-year turnover is presented in the maps in Figure 4.4. The turnover rate is computed for all time periods but the first. In the first

[5] Information are extracted from the database provided to the European Commission by AGEA (Agenzia per le Erogazioni in Agricoltura). The data are a courtesy from Associazione Alessandro Bartola. Further information can be found in *La spesa PAC in Italia (2008-2014)* (Sotte and Baldoni, 2016).

time period the turnover rate is assumed to be zero. Two patterns arise from the visual inspection of the maps. First, some years are associated with a higher turnover rate, and secondly some NUTS3 are associated with a higher turnover rate over the full time period. Particularly high was the turnover rate in 2014, 2012 and 2010. The inspection of the turnover rate is useful because a widely changing sample is expected to be associated with more volatile output, input and productivity indexes due to the random nature of the sample.

The second exogenous variable considered is the yearly percentage deviation of the estimated rainfall levels with respect to a long-time trend[6] (Funk et al., 2014) aggregated at NUTS3 level. The long-time trend used is the average aggregate rainfall of the period 1981-2004 for each NUTS3.

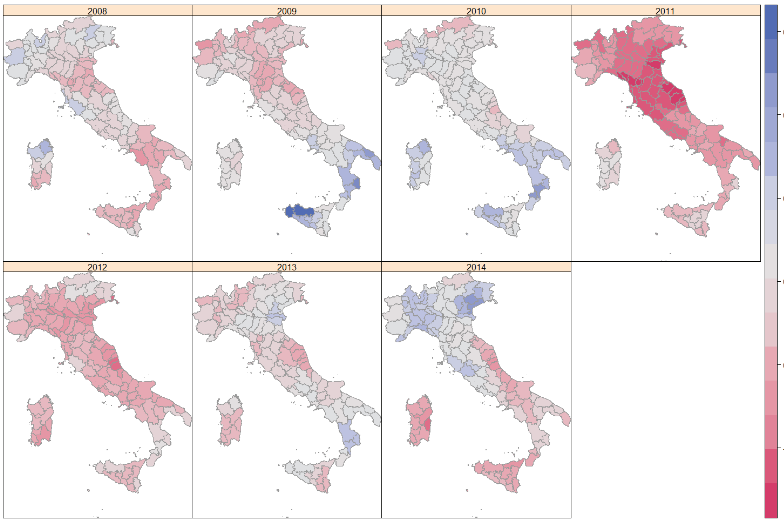

Figure 4.5: Percentage deviation of rainfall from long-time trend by NUTS3

Data on the percentage deviation are presented in Figure 4.5. The percentage deviation from the long-time trend is generally positive and high across the country in 2008, 2009, 2010, 2013 and 2014. In 2011 and 2012 rainfall levels seem less spread around the 1981-2004 trend and sometimes are lower than the long-time trend.

The third variable included consists of the number of hectares of Utilized Agricultural Area per NUTS3. These are presented in Figure 4.6. The NUTS3 with more UAA are mostly found in Puglia, Sicilia, Sardegna,

[6]Rainfall data are provided by the Climate Hazards Group of the Department of geography at the University of California at Santa Barbara in collaboration with the USGS Famine Early Warning Systems Network

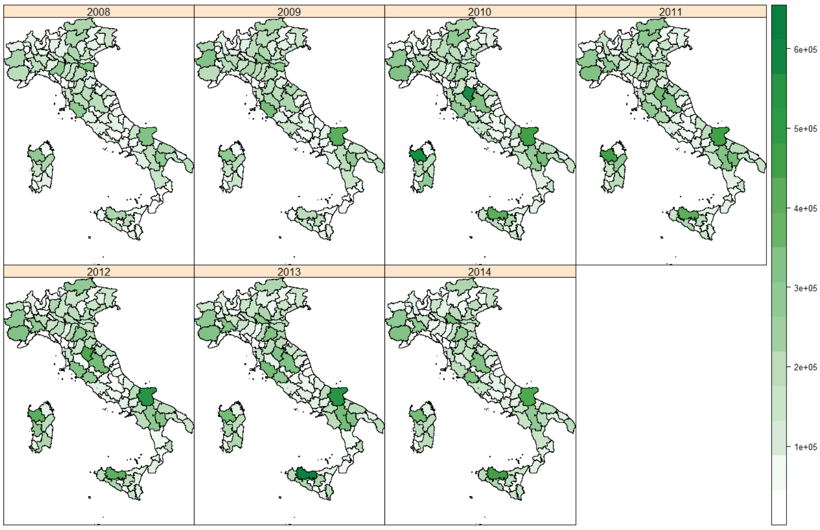

Figure 4.6: Number of UAA in hectares by NUTS3

Toscana and Piemonte. On average, NUTS3 with a low number of UAA are located in Liguria.

The share of UAA located in plain areas are presented in Figure 4.7. Regions with a higher density of plain areas are Emilia Romagna, Lombardia, Veneto and Puglia. The share of the plane UAA in some of their NUTS3 is above the 90% of their total UAA. In contrast, the share of UAA located in plain areas is very small in NUTS3 in Sicilia, Sardegna, Toscana and Valle d'Aosta. In some locations, these shares are below 5% of the total UAA.

Figure 4.8 presents the share of UAA in NUTS3 belonging to farms with large economic size. On average, NUTS3 with highest shares are located in Lombardia, Toscana, Piemonte and Emilia Romagna. NUTS3 with a low share of agricultural land belonging to large farms are mostly located in the Central and Souther parts of the country. A share below 15% is found in NUTS3 in Abruzzo, Campania, Calabria, Molise. NUTS3 with a low share are also found in Liguria, Alto Adige, Friuli Venezia Giulia and Toscana.

Additional information on the composition of NUTS3 agricultures is found in Figure 4.9. Here, the share of UAA belonging to small farms is presented. The maps show that small farming practices are located in Liguria, Marche, Toscana and in the Southern part of the country. In the South, high concentration of small-farms are found in Calabria and Campania and Puglia.

Figure 4.10 shows the average elevation of agricultural plots of FADN farms. An average elevation above 1000 meters is found in Valle d'Aosta,

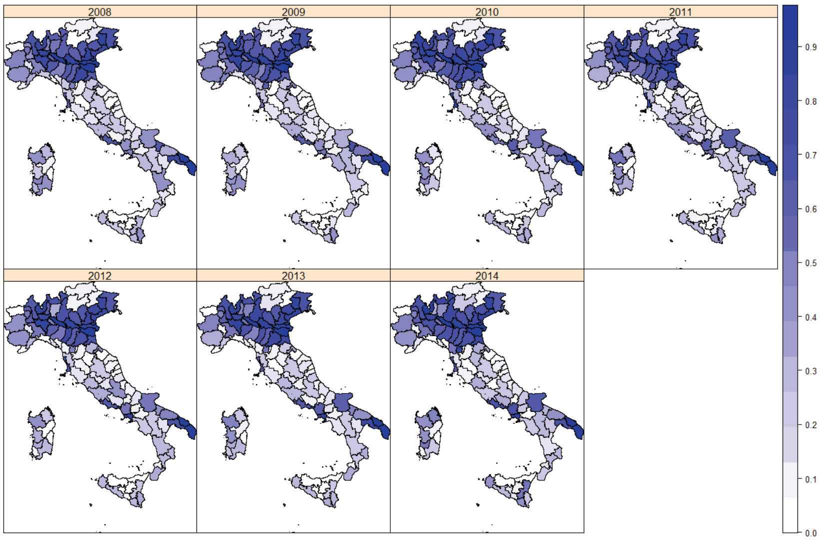

Figure 4.7: Share of UAA located in plains by NUTS3

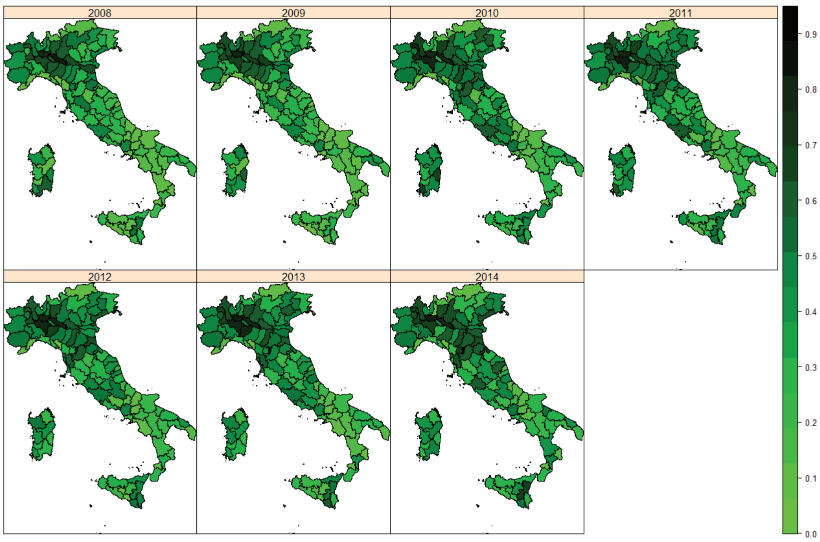

Figure 4.8: Share of UAA belonging to large farms

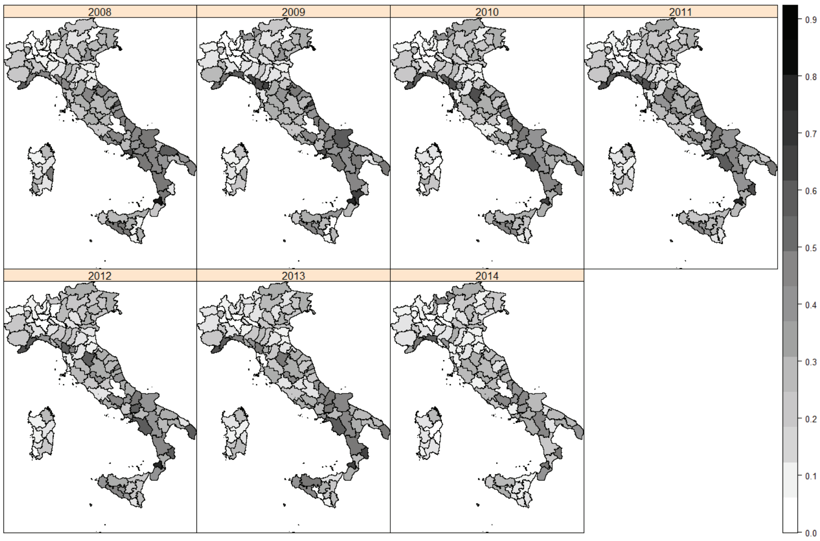

Figure 4.9: Share of UAA belonging to small farms

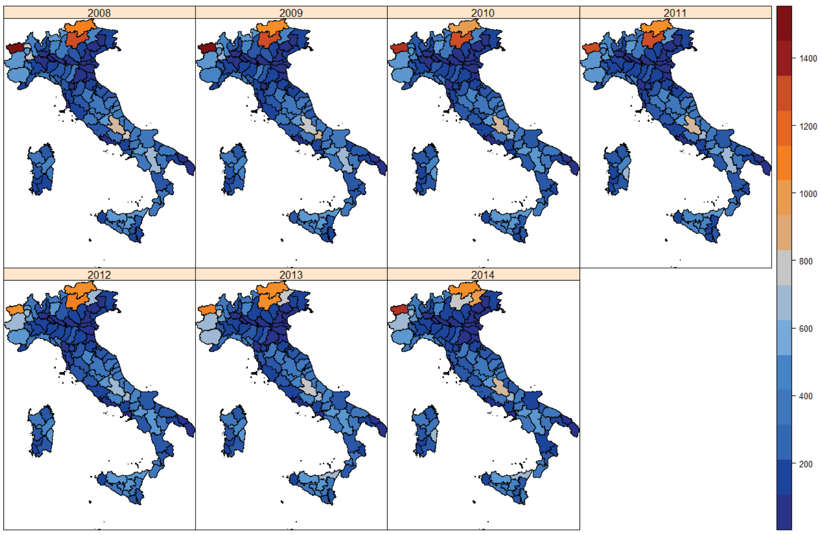

Figure 4.10: Average elevation of UAA

Trentino and Alto Adige. Average levels below 1000 meters and above 600 meters are found in NUTS3 Abruzzo, Molise, Veneto, Basilicata and Piemonte. Lowest elevation levels are found in some of the NUTS3 in Veneto, Lombardia, Toscana, Emilia Romagna and Friuli Venezia Giulia.

4.4 Space-Time Model

To model the diffusion process of agricultural TFP, the space-time dependence of TFP levels of NUTS3 is used. This level of analysis was considered the most appropriate for the job at hand because NUTS3 represents the most granular level available that covers systematically all territories in Italy. The level of analysis avoids aggregation biases of coarser spatial levels. By having a full coverage of the Italian land, it was possible to use the statistical tools available to model processes in space and thus, it was possible to study the diffusion process of productivity.

Space-time dependence of TFP is obtained by estimating a dynamic spatial linear relation. The relation is the following:

$$y_t = \phi y_{t-1} + \delta W y_t + X_t \beta + \epsilon_t$$

where y_t contains the information regarding relative productivity levels for the 107 provinces at time t in logarithmic form, y_{t-1} is the temporal lag of the productivity levels, W is the spatial weight matrix, X_t is a matrix containing the exogenous variables and ϵ_t is the random component assumed normally distributed with mean zero and variance σ^2. The error is assumed to be not serially and not spatially correlated.

The estimation of the parameters is carried out using the Bias Corrected LSDV (BCLDV) estimator based on the work of Elhorst (Elhorst, 2010) and Yu, DeJong and Lee (Yu et al., 2008). The multi-step estimation procedure is presented in Appendix I using Elhorst's notation.

The coefficients estimates that will be used in the modeling of the diffusion process are selected among a set of alternatives. These alternative results were obtained by using the BCLSDV estimator in the estimation of the same linear specification but assuming different spatial correlation structures across NUTS3. Thus, what differed in the set of alternative results was the spatial weight matrix used. In each estimation, the matrix was defined as a row-standardized distance matrix where, for each spatial unit, neighbors were identified as the spatial units whose centroid fall within a certain radius from the reference centroid. The spatial weight assigned to each neighbor, before row-standardization, was equal to its distance from the reference centroid. The set of results were obtained by using a different radius length in the definition of neighborhoods. The set of radius lengths considered were all the unitary lengths comprised in the interval [40 km; 220 km]. Estimates of three selected models are presented in Table 4.1.

	km: 50 maxll: -1243.293		km: 61 maxll: -1243.299		km: 69 maxll: -1243.308	
	Estimate	Std.Err	Estimate	Std.Err	Estimate	Std.Err
$\hat{\phi}$	0.107	(0.0438)	0.105	(0.0438)	0.105	(0.0438)
$\hat{\delta}$	0.768	(0.0422)	0.751	(0.0438)	0.704	(0.0495)
$\hat{\beta}_{turnover}$	-0.052	(0.1246)	-0.046	(0.1246)	-0.040	(0.1246)
$\hat{\beta}_{deviation}$	-0.166	(0.1062)	-0.149	(0.1063)	-0.170	(0.1064)
$\hat{\beta}_{log\_UAA}$	-0.251	(0.0797)	-0.262	(0.0797)	-0.242	(0.0797)
$\hat{\beta}_{share\_plains}$	0.430	(0.3641)	0.441	(0.3642)	0.447	(0.3642)
$\hat{\beta}_{CAP}$	-0.00003	(0.00001)	-0.00003	(0.00001)	-0.00003	(0.00001)
$\hat{\beta}_{share\_large}$	1.049	(0.29579)	1.122	(0.2958)	1.099	(0.2958)
$\hat{\beta}_{share\_small}$	-0.351	(0.3060)	-0.211	(0.3060)	-0.221	(0.3060)
$\hat{\beta}_{share\_grazing}$	-1.004	(0.3330)	-0.917	(0.3329)	-0.897	(0.3329)
$\hat{\beta}_{elevation}$	0.001	(0.0009)	0.001	(0.0009)	0.001	(0.0009)
$\hat{\beta}_{elevation^2}$	-0.000001	(0.000001)	-0.000001	(0.000001)	-0.000001	(0.000001)
$\hat{\sigma}^2$	28.393	(0.3206)	28.167	(0.3193)	27.902	(0.3178)

Table 4.1: BCLSDV estimates

The three models were selected because they assume stationarity in space and time[7] and because they are associated with the largest values of the maximized log-likelihood function among all the alternative models estimated. A larger maximum of the log-likelihood implies an higher probability of observing the sample given the assumptions made. The three corresponding spatial structures use radius lengths of 50 kilometers, 61 kilometers and 69 kilometers respectively. These spatial structures are assumed to be time-invariant and are presented in Figure 4.11.

The three sets of estimates are similar to each other. The coefficients estimates associated with the temporal and spatial lags are all highly significant. However, while the temporal dependence does not change in the three models, the spatial dependence parameters changes slighlty. By increasing the radius length, the spatial dependence parameter decreases. Given the

[7]Stationarity in space and time is achieved when the sum of the absolute value of the spatial and temporal parameters is smaller than one.

$$|\hat{\phi}| + |\hat{\delta}| < 1$$

Following Elhorst (Elhorst, 2014), the condition is satisfied when the characteristics roots of the matrix $\phi(I - \delta W)$ are included in the interval $(-1, 1)$.

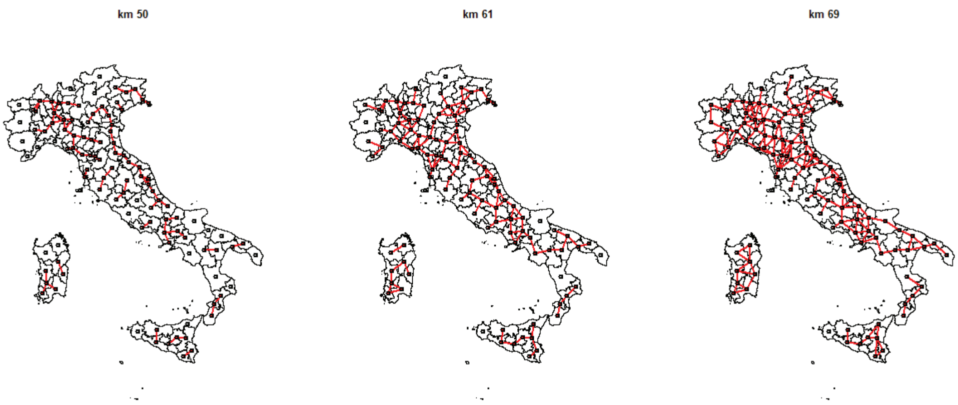

Figure 4.11: Spatial correlation structures with respectvely 50 km, 61 km and 69 km neighborhood radii

magnitude of their coefficients, it seems as if the spatial dependence is much stronger than the temporal dependence.

Coefficients associated with the exogenous variables help explaining the relationship. Those associated with the phisycal size of the NUSTS3 are negative and highly significant. This points to a negative relationship between TFP and physical size at NUTS3 level. The share of UAA located in plain areas is positevely related to the productive performance. However, the coefficient is not statistically significant in all three models. The coefficients associated with the share of land dedicated to large farms, to small farms and to farms spacialized in grazing livestock behave as expected: the share of land area dedicated to large farms is positively related to the productive preformance of NUTS3, while the share of small farms as well as the share of UAA dedicated to grazing livestock is negatively related to TFP. Neither these two latter coefficients are statistically significant at any level of confidence above the 90%. The average payment from the Common Agricultural Policy received by beneficieries located within NUTS3 is negatively related to productivity and its associated coefficient is statistically significant. However, given the complexity and diversity of the CAP support, this evidence should be investigated further before coming to any conclusions. Elevation has a non-linear concave relationship with TFP. On average for the three models, the relationship between elevation and producitvity is positive until around 500 meters elevation. Then, it starts declining.

For the modeling of diffusion in the next section, the model used is the one associated with the spatial weight matrix whose definition of neighborhood is based on a radius length of 50 km. This specification is selected because of its higher value for the maximized log-likelihood.

4.5 Productivity diffusion

Diffusion effects are obtained by using the space-time dependence structure estimated earlier using a radius length of 50 kilometers and by simulating a unitary shock hitting specific NUTS3. The effect of the unitary shocks hitting the locations spill-out to other NUTS3 over time. The positive contagion has a contemporaneous effect that reinforces the exogenous unitary shock in neighboring locations and has a temporal dimension over which the effect of the disturbance vanishes due to the stationarity.

Using the estimated econometric relation, it is possible to derive the *diffusion matrix*. The diffusion matrix is a matrix that contains the information on the space-time dependence of TFP of NUTS3 and is used to compute partial effects of explanatory variables. In this case, the diffusion matrix is obtained to quantify the partial effect of a random unitary productivity shock in specific NUTS3.

The diffusion matrix is obtained by backward substitution of the space-time relation as follows:

$$y_t = \phi y_{t-1} + \delta W y_t + X_t\beta + \epsilon_t$$

$$(I - \delta W)(-\phi L)y_t = X_t\beta + \epsilon_t$$

$$Qy_t = X_t\beta + \epsilon_t$$

$$y_t = Q^{-1}X_t\beta + Q^{-1}\epsilon_t$$

where, following Debarsy et al. (Debarsy et al., 2012) notation, Q is the space-time filter defined as follows:

$$Q = \begin{bmatrix} B & 0 & 0 & 0 & 0 & 0 \\ C & B & 0 & . & . & . \\ 0 & C & B & 0 & . & . \\ . & 0 & C & B & 0 & . \\ . & . & 0 & C & B & 0 \\ 0 & 0 & 0 & 0 & C & B \end{bmatrix}.$$

where $B = (I_N - \delta W)^{-1}$ and $C = -\phi I_N$. A productivity shock in the spatial unit $i = 1$ at time $t = 1$ has consequences for the same spatial unit and for the neighboring units over time. This cumulative effect (or spillover effect) at any time period is found by summing up the effects of the productivity shock for all spatial unit in each period considered as follows:

$$\sum_{k=0}^{T} \frac{\partial y_{t+k}}{\partial \epsilon_{i=1,t=1}} = Q^{-1} v_{i=1,t=1} \tag{4.1}$$

where $v_{i=1,t=1}$ is a vector of length Nk composed of all zeros elements but for the first spatial unit in the first time period. That non-zero element is equal to one and represents the unitary shock occuring to the spatial unit in the first time period.

Assuming a unitary shock hitting NUTS3 in every FADN region[8], we computed the cumulative spillover effect for each FADN region in a window of 20 years. Given the cumulative effects of a shock over these 20-period window, it is possible to establish a ranking of the most and least diffusive FADN regions. The ranking of the most diffusive ones is presented in Table 4.2. The cumulative diffusion effect is composed of all the effects that spill-out from NUTS3 of that specific FADN region to NUTS3 of other ones. Within regions spillovers are not included in the definition of the ranking.

The most diffusive FADN regions are Lombardia, Emilia Romagna, Veneto and Marche. The least diffusive ones are Alto Adige, Basilicata, Calabria, Puglia, Sardegna, Sicilia, Trentino and Valle d'Aosta. This latter group is composed of regions that, due to the narrow spatial correlation structure assumed, do not have any spatial connections with any other regions.

To describe the diffusion process of agricultural TFP, we focus on one of the most diffusive region that is located in the central part of the country, Emilia Romagna[9]. Assuming a unitary productivity shock in each of the NUTS3 in the region, we observe how the shock spreads to other locations and how it behaves over time. Results are presented in the form of maps, impulse response functions and spillover effects[10] in Figure 4.7, Figure 4.8, Figure 4.9 and Figure 4.10.

[8]FADn regions correspond to the NUTS2 classification but for Trentino-Alto Adige. In the FADN classification, Trentino-Alto Adige is split into two separate regions, Trentino and Alto Adige.

[9]Results concerning the diffusion process assuming a unitary shock in the NUTS3 of other regions are contained in Appendix J.

[10]The impulse response functions and spillover effects are presented without confidence intervals. An important development of this work will be to derive the confidence intervals for those curves using the bootstrap method.

Region	Spill-out
Lombardia	27.176
Emilia Romagna	26.858
Veneto	14.598
Marche	13.466
Toscana	11.095
Piemonte	10.451
Campania	7.803
Molise	6.518
Abruzzo	6.514
Friuli Venezia Giulia	5.707
Umbria	5.449
Lazio	3.231
Liguria	1.625
Alto Adige	0.000
Basilicata	0.000
Calabria	0.000
Puglia	0.000
Sardegna	0.000
Sicilia	0.000
Trentino	0.000
Valle d'Aosta	0.000

Table 4.2: Ranking of FADN regions by spill-out

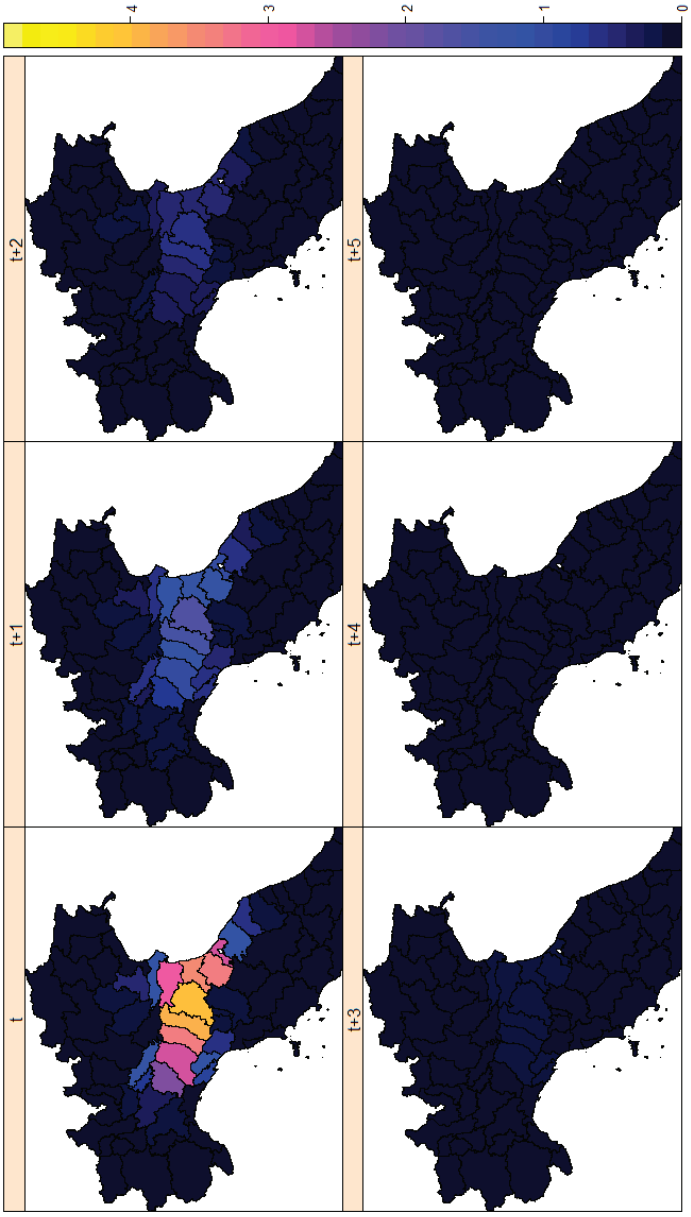

Figure 4.12: Geographical representation of the effects of a unitary productivity shock in NUTS3 in Emilia Romagna

An interesting point of view is given by the impulse response functions for each NUTS3 in Emilia Romagna presented in Figure 4.8. They represent the temporal profile of the effect of the shock for each NUTS3.

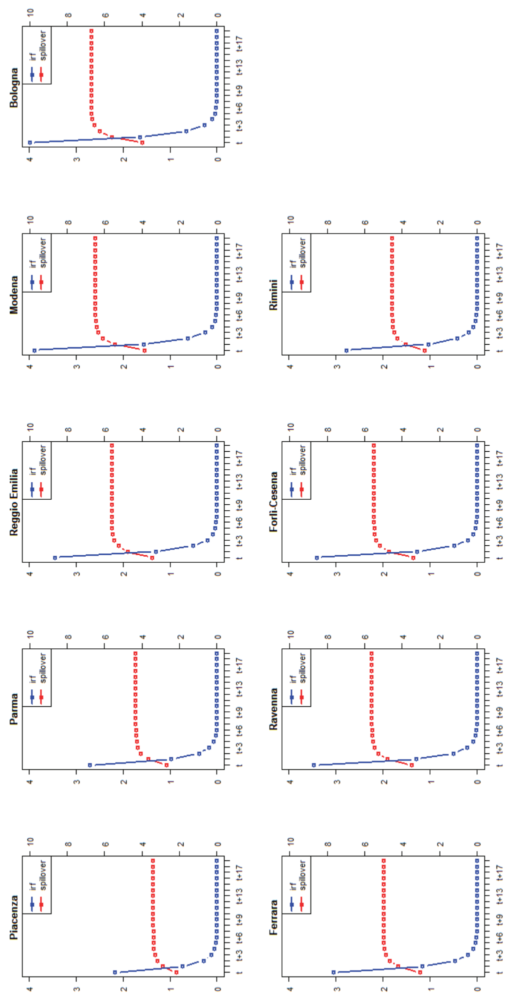

Figure 4.13: Impulse response functions and spillover effect for NUTS3 in Emilia Romagna

Two features are worth noticing. First, the contemporaneous endogenous spillover effect of neighbors adds up to the exogenous shock in each NUTS3. This can be seen by looking at the level of the shock in the first time period. For all NUTS3, these effects are larger than one due to the contemporaneous spatial spillover effect of neighbors. The second feature that is worth noticing is the time span over which the shock fades away. After five time periods, the effect is mostly absorbed and is close to zero. The cumulated values of the impulse response functions define the spillover effect of the initial shock at any time period and are represented by the red dotted line. It can be seen that, due to stationarity, the spillover effect in each NUTS3 increases over time and stabilizes in the long-run to an equilibrium level, i.e., the long-run spillover effect of the productivity shock. This equilibrium level is reached after around five years.

Due to the spatial link structure assumed, NUTS3 in one location are indirectly connected to other NUTS3 in locations even if these latter ones are far away. Given these assumed interdependence, the effect of the productivity shock reaches locations far from the epicenter of the shock over time.

The effects in Lombardia of the shocks in Emilia Romagna are represented by the impulse response functions in Figure 4.9. Here, three main features emerge. The first regards the magnitude of the shock. Due to the distance to the centroids from where the exogenous shock occurred, the magnitude of the shock in NUTS3 in Lombardia is typically much lower than the unitary exogenous shock. The second feature is that the indirect effect of the shock, in some NUTS3, does not always decrease. In the first time period in some NUTS3, it reinforces and only from the second time period starts decreasing. The third feature is that, due to the assumed spatial relations across NUTS3, positive externalities do not reach all NUTS3. Sondrio is not linked, neither directly nor indirectly, to NUTS3 in Emilia Romagna and it is not influenced by the shocks.

Figure 4.10 presents the impulse response functions of NUT3 in Abruzzo. Abruzzo does not share boundaries with Emilia Romagna and the effects of a shock in Emilia Romagna can be transmitted indirectly through its neighbors.

The impulse responses show different patterns with respect to the ones for NUTS3 in Lombardia. Due to the link structure across NUTS3, a unitary productivity shock in Emilia Romagna spreads to all NUTS3 in Abruzzo. The shock increases for all NUTS3 in the first two time periods and then starts fading towards zero. The long-run spillover effect is much lower than those locations closer to the epicenter of the shock. The peak of the spillover effect is reached after around eight years.

Maps showing the diffusion process in space and time assuming a unitary shock hitting NUTS3 of other regions in Italy are presented in Appendix J.

Using the same 20-year window we computed the effects of a unitary shock hitting every NUTS3 in Italy. Then, we ranked them in terms of how much they spill-out and how much they absorb from shocks occuring in other NUTS3, i.e., their spill-in. By assuming a unitary shock in each NUTS3, we ranked NUTS3 based on the cumulative effect of the productivity shock in

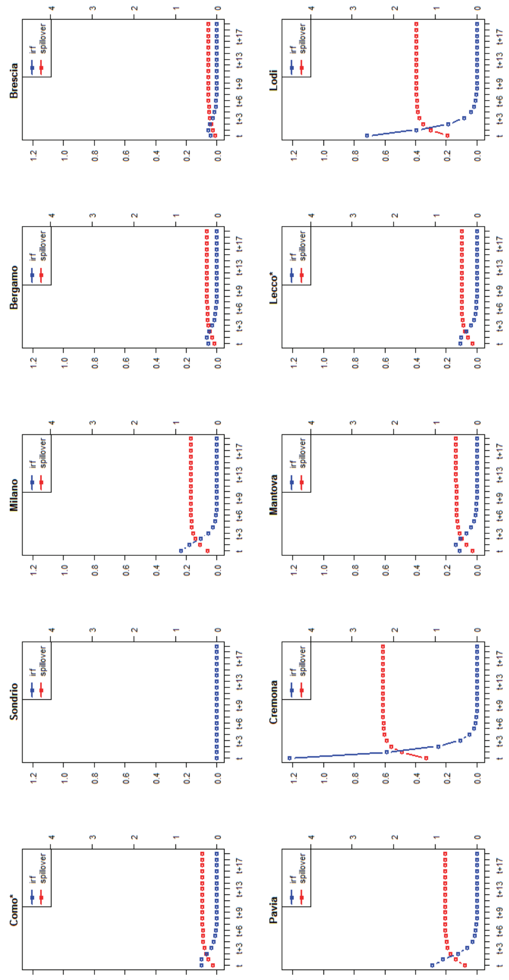

Figure 4.14: Impulse response functions and spillover effect for NUTS3 in Lombardia

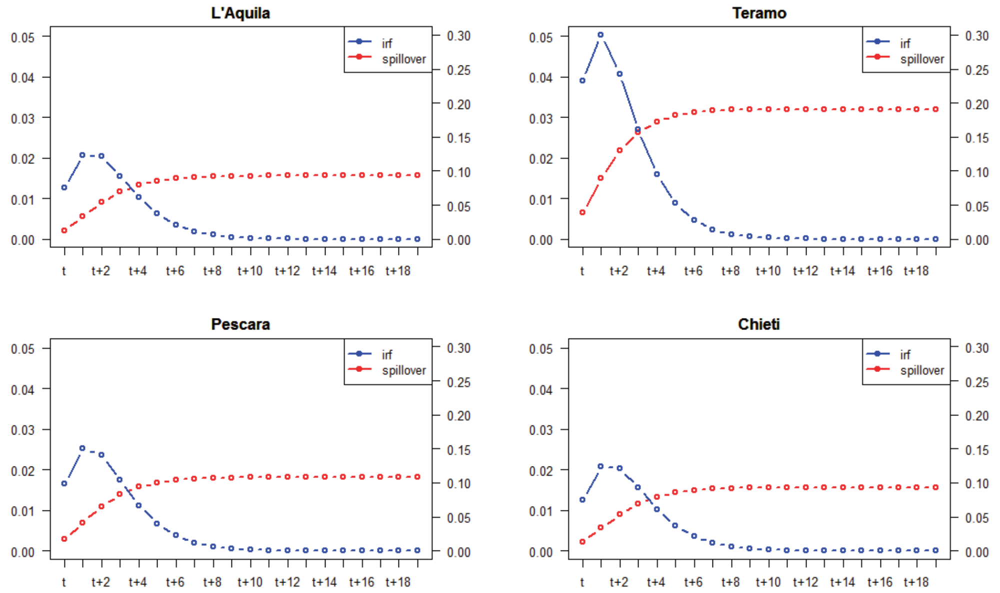

Figure 4.15: Impulse response functions and spillover effect for NUTS3 in Abruzzo

every other NUTS3 in twenty years. The list of the ten most diffusive NUTS3 is found in Table 4.3.

The most diffusive NUTS3 are Medio Campidano, Caserta, Milano, Pescara, Lodi, Parma and Massa-Carrara. The least diffusive ones are all NUTS3 that do not have any connections with any other NUTS3 as visible in Figure 4.6.

Then, for every NUTS3, we assumed a unitary shock hitting all other Italian NUTS3 and computed the cumulative effect occurring within the first NUTS3. We labeled this cumulative effect as the total spill-in. The most absorptive NUTS3 are presented in Table 4.4.

The maps of the most diffusive and most absorptive NUTS3 is presented in Figure 4.11. Values are normalized within the interval [0,1] to allow for a better visualization.

In terms of spill-out, the most diffusive NUTS3 are located mostly within the Northern and the Central regions. In the North, high levels of spill-out are delivered from NUTS3 in Piemonte, Lombardia, Veneto and Friuli Venezia Giulia. In the Center, high levels of spill-out are found for NUTS3 in Emilia Romagna, Marche, Abruzzo and Toscana. Highly diffusive NUTS3 are also found in Campania and within both islands. The highest level of spill-out is registered in Sardegna.

In terms of spill-in, NUTS3 are more homogeneous. Due to the spatial

NUTS3	Spill-out
Medio Campidano	1.000
Caserta	0.991
Milano	0.962
Pescara	0.909
Lodi	0.886
Parma	0.847
Massa-Carrara	0.813
Novara∗	0.767
Macerata	0.735
Piacenza	0.732
Pavia	0.715
Pistoia	0.684
Udine	0.677
Como∗	0.673
Siena	0.667

Table 4.3: Ranking of NUTS3 by spill-out

NUTS3	Spill-in
La Spezia	1.000
Cremona	0.953
Fermo	0.943
Napoli	0.941
Como∗	0.934
Lecco∗	0.932
Trieste	0.931
Reggio Emilia	0.929
L'Aquila	0.929
Asti	0.928
Biella	0.926
Chieti	0.925
Vercelli	0.923
Pavia	0.921
Teramo	0.920

Table 4.4: Ranking of NUTS3 by spill-in

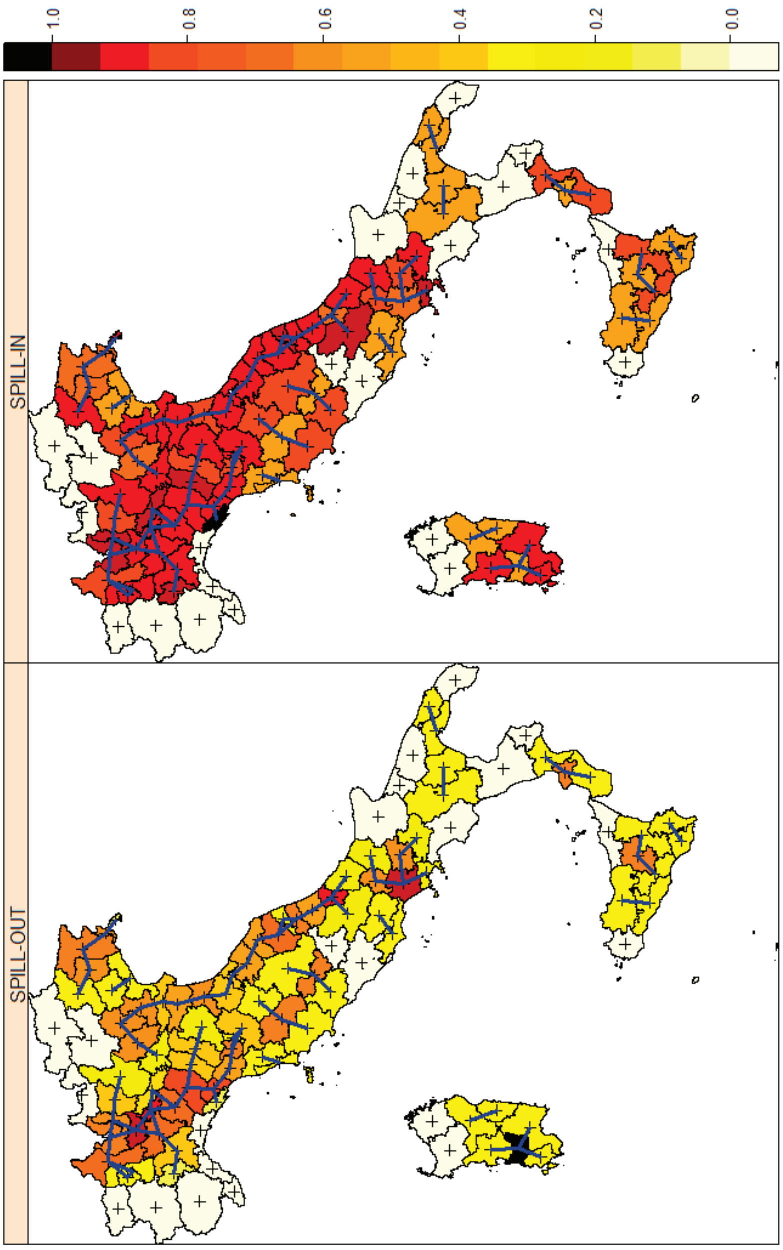

Figure 4.16: Maps of NUTS3 by spill-out and by spill-in

correlation structure, there seems to be a large cluster of highly absorptive NUTS3 running from the Northern regions to the Adriatic coast to Campania. Low levels of absorptivity are found in NUTS3 across Basilicata and Puglia. Relatively high and low levels of absorptivity are found within the two islands, especially within Sardegna.

4.6 Conclusions

This paper explores the spatial and temporal properties of agricultural TFP measurements derived at a spatially disaggregated level in Italy. It is shown that a low degree of productivity clustering exists across the country and that productivity clusters are geographically limited. Space-time dependence of productivity levels for NUTS3 is estimated in a dynamic spatial panel data model. Space-time dependence is then used to quantify the expected diffusion effects of a productivity shock hitting NUTS3 in Italy. Due to the low degree of time dependence and to the narrow correlation structure embedded in the selected spatial weight matrix, the effects of a shock spread significantly only to contiguous regions. The spillover effect is positive also for NUTS3 that are not directly connected to the source of the shock but is much smaller in magnitude. The shock has an immediate impact for those NUTS3 close to the epicenter of the shock and tends to fade in few time periods. The impact of the shock increases in magnitude over time for the NUTS3 far away from the sources of the shock. For these regions, these effect reaches its peak in two time periods and then starts fading to zero. The maximum spillover effect follwoing the producitvity shock is attained after around eight years.

We bring forward these evidences to support the idea that agricultural production is a site-specific production process that is highly influenced by those economic and climatic conditions that are geographically limited. These specific conditions of locations influence their agricultural production processes and tehcnology. As a consequence, the diffusion process of innovation is significantly low and limited, resulting in large productivity differentials even across neighboring regions.

A policy with the objective of promoting agricultural productivity growth in Italy should first recognize that large differentials exist. Then, it would channel investment into R&D and into instruments to promote the creation of on-farm innovation. Investing in specific locations could result in a higher return on investment rather than investing into other locations due to spillover effects. The most diffusive regions in Italy are Lombardia and Emilia Romagna followed at a distance by Veneto, Marche and Toscana. The least diffusive regions are Alto Adige, Trentino, Valle d'Aosta, Basilicata, Calabria, Puglia, Sardegna and Sicilia. A policy at regional level aimed at promoting agricultural productivity growth but subject to budget constraints should either target the most diffusive regions in Italy or increasing the absorptive capacity of the least absorptive ones.

The most diffusive NUTS3 in Italy are Medio Campidano, Caserta, Milano, Pescara and Lodi. The most absorptive NUTS3 are La Spezia, Cremona, Fermo and Napoli. A policy aimed at promoting productivity growth at NUTS3 level, with a budget constraint, could target those NUTS3 that have an higher capacity of channeling externalities to other locations. At the same time, the policy could use alternative policy instruments for increasing the absorptive capacity of the least absorptive ones.

Chapter 5

Discussion

The aim of this section is to summarize the results presented in the previous chapters and to discuss possible explanations for the evidences emerged. The main results of the whole research are the following:

- aggregate productivity is declining in Italy;
- there are wide productivity differentials across types of farming;
- there is a positive relationship between TFP and economic size;
- regional productive performances are not easily comparable;
- spillover effects are limited.

Aggregate productivity is declining in Italy

In Chapter 3, productivity levels at national level were derived using different definitions for the output index. Despite the fact that the output indexes were based on different assumptions, the time-series of aggregate productivity were remarkably similar. All four TFP indexes were trending downwards with an annual average rate of change ranging between -1.5% and -2.9%. A general downtrending behavior can be observed also when looking at the productivity indexes aggregated by type of farming and by economic size of farms.

The period of analysis spanning 2008-2014 might be too narrow to come to conclusions regarding long-term trending behavior of TFP. However, this evidence could be used to support the idea that productivity growth is slowing in developed countries in recent years.

Two possible explanations are discussed here. They are the innovative capacity of Italian agriculture and the effects of the 2003/2004 CAP Reform.

According to the Economic Research Service at the USDA, the main dirver of long-run TFP growth is technological innovation (Wang et al., 2015). Innovation can be spurred by both public and private R&D investments. However, the ability of adoption ultimately influence the impact of R&D investments. Both public infrastructures and extension services influence the speed of adoption and thus, they are critical drivers of producitvity growth.

A possible explanation for the seemingly poor performance in Italy in recent years can be found in the structural features of Italian agriculture. In particular, its endowment of human capital and ICT infrastructure coupled with the small average size of farms could affect the innovative capacity of the Italian agricultural system. De Devitiis and Maietta (De Devitiis and Maietta, 2013) compare the level of human capital in agriculture across European countries and found that Italy ranks very low in the list. In 2005, only 11.2% of Italian farmers have either a Basic or Full Agricultural Training[1]. They define such percentage as very low when compared to other EU-27 countries. Among European Member States, Italy ranks 21st. The Netherlands ranked first in the list with a 71.5% share of farmers with either Basic or Full agricultural training followed by Germany, Luxemburg and France with the 68.5%, the 55.9% and the 54.3% share respectively. De Devitiis and Maietta defined the agricultural education system in Italy as non-efficient and not attractive at any level (De Devitiis and Maietta, 2013).

The authors identified a second source of major deficiency in the Italian agricultural sector, i.e., the lack of ICT investments. They have found that merely the 3.8% of farms in 2010 owned ICT and 25% of them were located in Lombardia and Emilia Romagna (De Devitiis and Maietta, 2013).

The authors estimated that only a percentage of Italian farms ranging between 2% and 4% could be classified as innovative. In 2010, the kinds of innovation introduced were mostly related to new machinery, equipment and plants. Agro-energy was another important source of innovation. Major obstacles in innovating were identified as credit rationing, market instability and bureaucracy burden (De Devitiis and Maietta, 2013).

Besides the structural features of the Italian agricultural system, another potential driver of productivity growth in the period is represented by the effects of the 2003/2004 CAP Reform[2]. Esposti (Esposti, 2015) has shown

[1]According to the Farm Structure Survey of 2010 and of 2013, Italy ranks first in the list in both surveys with a share of farmers with either Basic or Full Agricultural Training above 95%. The remarkable improvement occurring over such a narrow time window casts doubts over the constancy of assumptions underlying these measurements. A further investigation would be required in order to verify what the sources of change are.

[2]The so-called Fischler Reform.

that the decoupling of subsidies under this reform has had a significant impact in re-orienting the production choices of farmers while it less clearly impacted investment decisions. Although the relationship between producitvity and the decoupling of subsidies should be investigated with appropriate tools before inferring its effects, the decline in aggregate agricultural productivity over the period 2008-2014 could represent a signal that the elimination of the distorting effects on production decisions has had no discernible impact in increasing productivity of Italian farms in the medium-term. This result, if confirmed, would be consistent with those presented by Rizov et al. (Rizov et al, 2013) and of Serra et al. (Serra et al., 2008).

There are wide productivity differentials across types of farming

Productivity indexes aggregated at the level of types of farming point to large productivity differentials across sectors. On average during the sever-year period, the dairy sector was the most productive sector followed by horticulture, wine and fruits production. The least productive farms were those specialized in grazing livestock, cereals, mixed crops and livestock, and granivores. In 2008, dairy farms were almost two times more productive then those specialized in cereals production. In 2014, the farms specialized in wine production were more than two times more productive than those specialized in grazing livestock.

These productivity differentials could be the reflection of technical and organizational features of the production process specific to each sector. Huffman and Evenson (Huffman and Evenson, 2001) suggested that some specific agricultural sectors, such as the livestock sector, tend to be less dependent on seasonal and spatial constraints, and are more reliant on fixed production plants. All these features make these production processes similar to those typical of the manufacturing sector with the consequence that workers can specialize in a particular phase of production and be more productive (Huffman and Evenson, 2001). Overall, agricultural businesses associated with higher degrees of specialization, with a less risk averse behavior and with an higher paid-to-unpaid labor ratio tend to show hgher levels of technical efficiency (Barnes et al., 2010). Sheng et al. (Sheng et al., 2016) interprets risk aversion as the capacity and willingness to adopt alternative input mixes, management practices and technologies. Claiming that the elastcity of substitution between inputs is positively linked to productivity, they argue that farmers with higher educational levels are less risk averse, they may have higher elasticity of substitution and thus, are associated with higher productivity levels.

The productivity differentials observed among types of farming may be a consequence of the more enterpreneurial nature of some farm types. The dairy sector, the horticultural sector and the wine production sector can all be associated to a more professional nature of the business with respect to sectors such as arable crop and cerelas production. These latter ones are typically constrained by plant and soil biology as well as by climate. It is difficult for workers in crop production to be fully employed and to specialize in any phase of production (Huffman and Evenson, 2001).

There is a positive relationship between productivity and economic size

Results of Chapter 3 show a clear positive relation between economic size and productivity. Such a result could be explained by the presence of increasing returns to scale in Italian agricultural production.

In the literature, there is a long standing debate on the relationship between size and productivity in agriculture. The debate is characterized by two main views: one that argues in favor of a negative relationship between physical size and productivity and the other that argues in favor of a positive relation between economic size and productivity. Both views are not necessarily constrasting and are highly influenced by the definition of productivity and of farm size.

- *Negative relation between physical size and productivity*: the idea that a negative relationship exists between farm physical size and productivity - defined as land productivity - has almost become a stylized fact in the economic development literature (Townsend et al., 1998). Since the work of Sen (Sen, 1966), the explanations put forward to justify this stylized fact were related to specific features characterizing imperfect markets in developing countries. In particular, the main argument supporting the theory was the higher incentive of family labor to work intensively with respect to hired labor (Feder, 1985; Chen et al., 2005; Thapa 2007). Over time, the idea of such a negative relationship has been challenged on the grounds of omissions of important variables such as soil quality or the presence of measurement errors (Barrett et al., 2009), or because it was considered flawed by the usage of partial productivity measurements (Townsend et al., 1998; Helfand and Levine, 2004). When including the aforementioned omitted variables or when using total factor productivity measurements, the inverse relationship seems to loose significance (Townsend et al., 1998; Helfand and Levine, 2004).

- *Positive relation between economic size and productivity*: studies regarding the relationship between economic size and productivity are typically focused on agricultural systems in developed countries. Results point to a positive relationship between productivity and measures of economic size such as total output, total input, assets value, gross farm income (Huffman and Evenson, 2001; Mugera and Langemeier, 2011; Sheng et al., 2016). The main explanations for such a positive relation can be found in the underlying common drivers of TFP and size, and in the higher probability for larger farms to access critical resources. Using a theoretical model, Sheng et al. (Sheng et al., 2016) show that both farm productivity and farm size are positively related to TFP. In the presence of a reduction in the relative price of capital to labor, farms with the ability to adjust their input mix tend to be more productive and larger due to the so-called "income-effects" (Klump and de La Grandville, 2000; Sheng et al., 2016). Arguments in favor of the positive relation between size and productivity is linked to increased revenue per unit output and reduced costs due to: efficient access to information, better marketing decisions and opportunities for vertical integration with an input supply business (Huffman and Evenson, 2001). Additional arguments supporting the view are related to the possibility for large-sized farms of gathering resources through more modern and flexible contracts and because those farms are more likely to be endowed with a high level of human capital (De Devitiis and Maietta, 2013). Restricted access to different production factors may limit innovative capacity and influence productivity differentials (Restuccia et al., 2008; De Devitiis and Maietta, 2013).

The two arguments presented are not necessarily constrasting becuase economic size and physical size do not coincide in agriculture. Depending on the types of activities carried out, there may be farms with large physical size but with small economic size and vice versa. A typical example of farms associated with a small physical size but large economic size is represented by horticulture specialists. In Italy, these farms are concentrated in Liguria and produce high value crops under greenhouses or in industrial gardens on limited land areas. Due to the high unit value of those crops, their economic size is large while their physical one is small. On the contrary, arable crops and cereals specialists tend to carry out their activities on larger areas but their output value per hectare may be relatively small when compared to horticulture specialists limiting their economic size.

In the present research, economic size of farms is a function of their Standard Output. Standard Output is a proxy for the potential average output of farms in each location. Results show a clear positive relationship between economic size and TFP in Italy thus confirming the prevalent literature on the relation between economic size and productivity in developed countries.

Regional productive performances are not easily comparable

In Figure H.2 of Appendix H, productivity indexes, their HP filtered series and their mean trends are presented for FADN regions in Italy. All productivity statistics present a large degree of variability within the period. Some regions such as Sardegna, Emilia Romagna and Puglia seem to exhibit an uptrending behavior. Some others such as Liguria and Valle d'Aosta seem to exhibit a downtrending behavior. However, some regions such as Lombardia, Marche, Lazio and Friuli Venezia Giulia show complex trends and it is difficult to compare their evolution in the period considered. The complexity of the figures might be attributable to the different composition of the regional agricultures as well as to idiosyncratic factors affecting each region in every time period.

By averaging out productivity indexes over time, a simpler but possibly misleading picture emerges. In Chapter 3, section 3.5, regions were classified into three groups of different levels of average productivity. Alto Adige, Trentino, Veneto, Lombardia, Friuli Venezia Giulia, Emilia Romagna, Calabria and Basilicata were clustered into the group of highly productive regions. Piemonte, Toscana, Umbria, Marche, Lazio, Molise, Puglia and Sicilia were classfied as regions with an intermediate level of productivity. Lastly, Valle d'Aosta, Liguria, Abruzzo and Sardegna were classfiied as less productive regions. Then, the composition of the regional agriculture was inspected.

Most of the highly productive regions from Northern Italy are associated with highly productive specializations. For example, Lombardia, Alto Adige and Emilia Romagna are highly specialized in the dairy sector. Trentino and Alto Adige are highly specialized into fruit production. Wine production is a major specialization in Friuli Venezia Giulia, Veneto and Trentino. Especially in Lombardia and Emilia Romagna, most activities are concentrated into farms of large economic size. Moreover, levels of human capital are typically higher in the Northen part of Italy. In 2010, the percentage of farmers with an agriculture-specific tertiary education were higher in Lombardia, Emilia Romagna and Umbria (De Devitiis and Maietta, 2013). Lombardia, Emilia Romagna together with Toscana are also the leading regions in Italy in the use of ICT insfrastructure. Furthermore, the features of the Italian agriculture seem to be clearly linked with territorial development models (De Devitiis and Maietta, 2013). Given these evidences, it does not surprise that most highly productive regions are those located in the North. What surprises instead is the presence of Basilicata and Calabria in the list of most productive regions. Basilicata is not highly specialized into specific sectors and presents an almost equal composition in terms of economic classes of farms. Calabria has a very high concentration into the olives and oil production sector and its activities are carried out primarily in small farms. Sources of their remarkable performance could be found outside the dimensions of specialization and economic size. According to De Devitiis and Maietta, Basilicata and Calabria have specific features that differentiate them from the rest of the country. Both regions are the leading Italian regions in terms of the share of UAA dedicated to organic farming. This farming type can be explained by the regional public support, by private action, and by better climatic conditions (De Devitiis and Maietta, 2013). An additional features that distinguish the farmers population in Calabria could be the presence of a large share of young farmers. In 2012, the percentage of youth-run farms in Calabria was around 14% against a national average of 6.7%. A younger farming population could be associated to more educated farmers, less risk averse behavior and more innovative agriculture. These features could be the source of their production performance.

For what regards the group associated with an intermediate average level of productivity, it is made of regions located either in the North, in the Center and in the South. The composition of their agriculture is rather diversified and concentrated in small farms except for Toscana and Piemonte. These two regions are specialized into highly productive sectors and concentrate their activities into large farms. Intuitively, one would expect them to lead in terms of productive performance. However, this is not the case. A deeper investigation would be required to explain their rather disppointing performance.

Group three is composed of less productive regions. Three of them, namely Valle d'Aosta, Liguria and Sardegna, are highly specialized into a single sector. They are specialized in the dairy sector, horticultural sector and in the grazing livestock sector respectively. Abruzzo is specialized into wine production, horticulture, and arable crops production. Except for Sardegna, the composition of the agricultures of this group of regions is approximately balanced across farm size classes.

A first attempt to explain regional productivity was to measure the correlation coefficients between TFP levels and the concentration of activities by types of farming and size classes. Some intersting insights can be extracted from these summary statistics. However, more complex modeling approaches would be required before being able to descrive the dynamics of productivity.

A possible line of investigation would require the derivation of producitvity indexes that take into account the regional dimension as well as the type of farming and the size classes of farms at the same time. Such indexes would be useful in comparing the production performance of farms operating in different regions holding their economic size and their type of farming equal. An example is given in Figure 5.1.

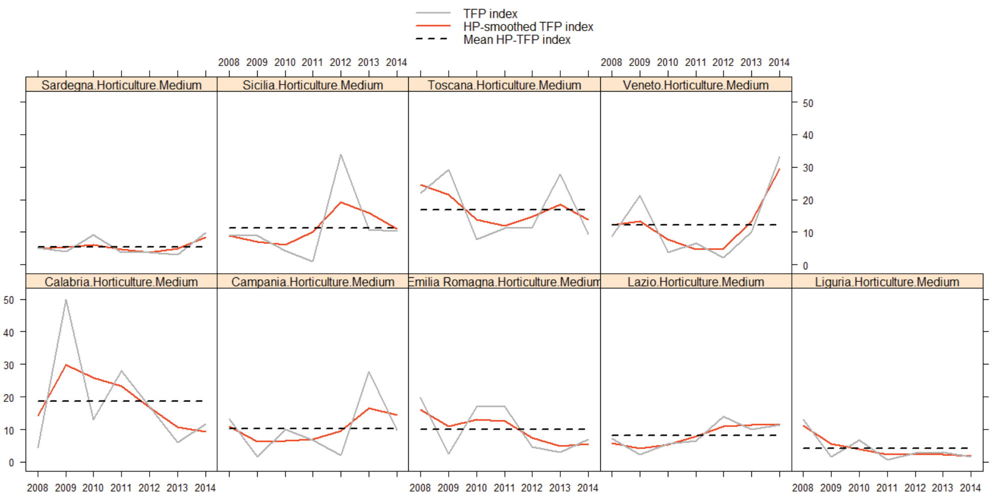

Figure 5.1: Regional level productivity for medium-sized farms specialized in horticulture

Figure 5.1 shows that, the productive performance of medium-sized farms specialized in horticulture differs remarkably across regions. Such productivity differentials may not be attributed to differences in accessible physical technology and in the organization of the production processes of the spatial units, as they are all engaged in the same farming type and using the same scale of operation. Thus, sources of productivity differentials could be represented, for example, by differences in operating environment or in management practices. A thorough investigation using this level of analysis could be extremely useful in deriving policy advice.

Spillover effects are limited in space

In Chapter 4, the spatial properties of productivity measurements were investigated at NUTS3 level. The level of analysis was selected to take into account, as much as possible, of the spatial heterogeneity of the Italian territory. This could be particularly relevant when dealing with aggregate production functions in agriculture where crop and animal biology plays a major role. Neglecting specific seasonal and spatial features of locations, that in turn influence the biology of crops and animals, could give rise to biased conclusions.

Moran spatial autocorrelation tests were carried out in each of the accounting years considerd. Those tests were pointing to a limited degree of spatial autocorrelation of productivity at NUTS3 level. When detected, spatial autocorrelation was higher when using a very narrow definition of neighborhood. When this definition was broadened by increasing the radius length, the spatial autocorrelation coefficients tended to decrease.

A similar insight was extracted from the iterative estimation of a space-time autorgressive panel data model controlling for covariates. The spatial weight matrixes used were time-invariant row-standardized distance matrixes with a cut-off value in the definition of neighbors. Assuming normality, the maxima of the alternative log-likelihood functions were higher using neighborhood radii comprised in the interval of 50 - 70 kilometers. When the radius length in the definition of the spatial weight matrix was increased to over 120 kilometers, the BCLSDV estimates of the spatial dependence were explosive or non-significant.

The use of a distance matrix with a cut-off value in the definition of a time-invariant spatial weight matrix can be questioned. As there is no consensus over how to define a-priori a spatial weight matrix in econometric models, anyone could come up with arguments supporting an alternative definition of the spatial correlation structure. In this analysis, the distance matrix was selected based on theoretical and empirical grounds. This type of matrix used a spatial correlation structure that is consistent with the nexus between spatial agglomeration and knowledge spillover (Cardamone, 2014). The closer two producing units are, the higher is the probability of existence of a certain degree of interdependence betweeen them. This effect was considered to be limited in space by introducing a cut-off value in the definition of neighbohoods. The cut-off value was introduced also on empirical grounds. In fact, it was difficult to estimate a stationary space-time model when using a full distance matrix. Further, the specific cut-off value was selected based on the maximum value of the maximized log-likelihood functions.

The evidences emerged from the spatial autocorrelation tests and from the estimation of the space-time models were used to support the idea that the agricultural production process in Italy is highly site-specific. According to De Devitiis and Maietta, there is a process of productive specialization in Italy at regional and even at sub-regional level. Geographical features as well as the interconnection with territorial development models define a clear geographic differentiation of agricultural production activities (De Devitiis and Maietta, 2013).

Further evidence on the geographical specialization can be gathered by aggregating at NUTS3 level FADN information on production value of the most important agricultural products. The maps in Figure 5.2, Figure 5.3, Figure 5.4 and Figure 5.5 show the distribution of production value across NUTS3 of some of the most valuable Italian products. Only NUTS3 with a higher degree of specialization in those specific products are considered.

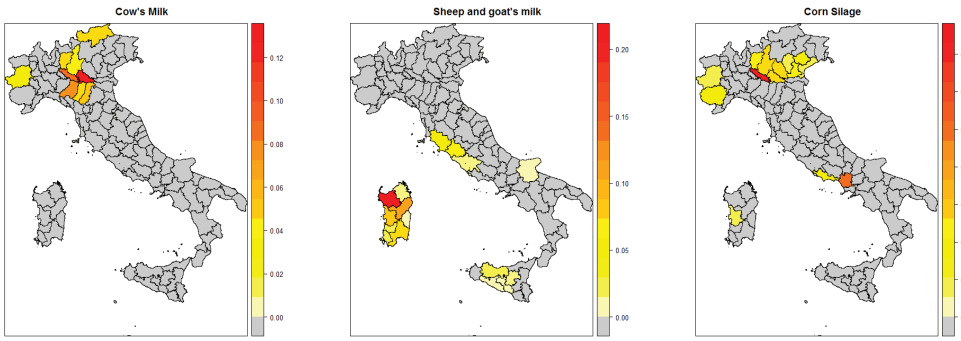

Figure 5.2: Shares of livestock related production value in most specialized NUTS3

From Figure 5.2, it can be seen that the production of cow's milk is concentrated in Lombardia and Emilia Romagna in the NUTS3 of Mantova, Cremona, Parma and Modena. Milk from sheeps and goats is produced for a share of over 50% in Sardegna in the NUTS3 of Sassari, Nuoro, Oristano, Cagliari, Carbonia Iglesias and Medio Campidano. For what regards the production of corn silage, most of the activities are located in Lombardia and Veneto in the provinces[3] of Cremona, Verona, Mantova, Brescia and Padova.

Cereals production is carried out throughout the country. However, the production of specific cereals is concentrated in particular areas. Figure 5.2 shows the spatial distribution of the largest shares of hybrid maize, rice and durum wheat production value. Hybrid Maize is mostly produced both in the North-West and in the North-East. Piemonte Lombardia, Veneto and Friuli Venezia Giulia is where most of the production is located. NUTS3 most involved in the produciton of hybrid maize are Torino (Piemonte), Cremona, Brescia (Lombardia), Rovigo and Padova (Veneto). Rice production is concentrated in the North-West in the provinces of Pavia, Milano (Lombardia), Vercelli, Novara and Alessandria (Piemonte). Almost 50% of the production of durum wheat is located in Puglia, Marche, Sicilia, Basilicata

[3]Italian provinces correspond to the Eurostat NUTS3.

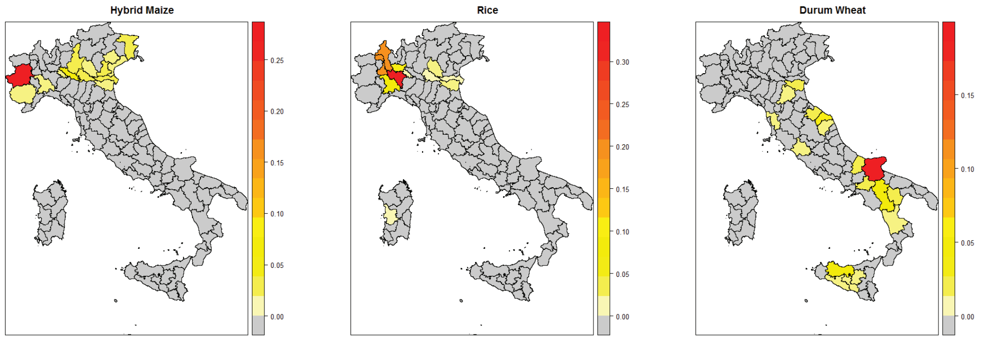

Figure 5.3: Shares of cereals production value in most specialized NUTS3

and Molise. NUTS3 most involved in the production of durum wheat are Foggia (Puglia), Ancona (Marche) and Palermo (Sicilia).

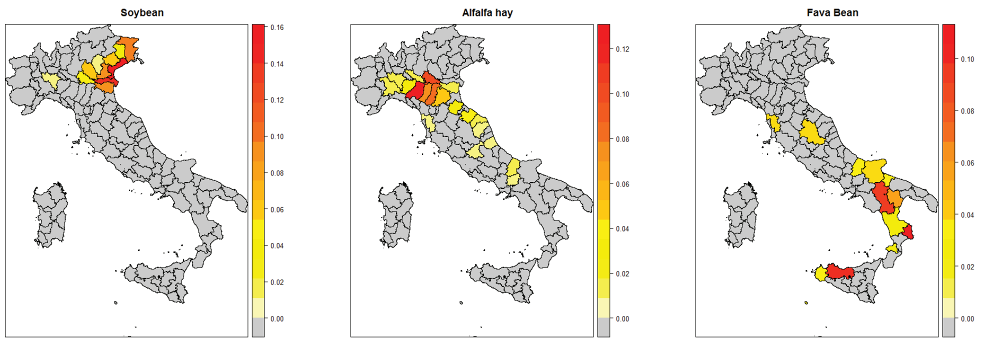

Figure 5.4: Shares of legumes production value in most specialized NUTS3

Figure 5.4 shows the distribution of the largest shares of the production value of the most important legumes. These are soybeans, alfalfa and fava bean. Their production is concentrated in the North-East, the Center, and in the South respectively. Production of soybeans is mostly located in the provinces of Venezia, Rovigo, Padova (Veneto), Udine (Friuli Venezia Giulia) and Ferrara (Emilia Romagna). Alfalfa hay production is concentrated in the provinces of Parma, Modena, Reggio Emilia, Bologna (Emilia Romagna), Mantova (Lombardia) and Pesaro Urbino (Marche). As for the production of fava beans, Crotone and Palermo (Calabria and Sicilia respectively) are the leading provinces in terms of produciton value. These two latter NUTS3 account for more than 20% of the fava beans production value of the whole period in Italy.

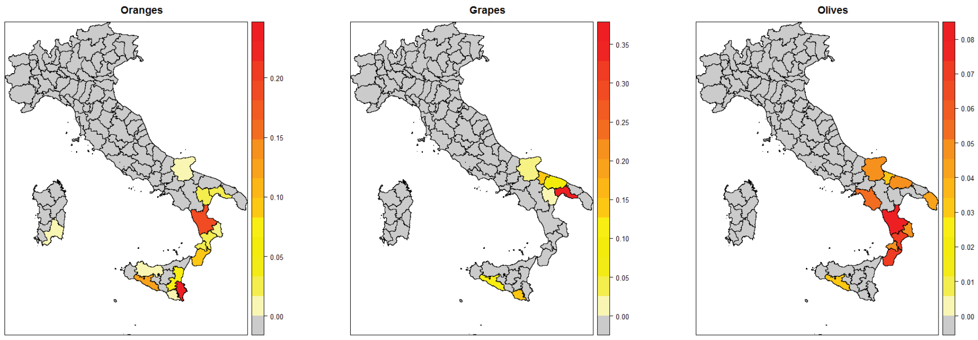

Figure 5.5: Shares of perennials production value in most specialized NUTS3

More than 40% of the total production value of oranges in the whole period 2008-2014 come from Sicilia. Almost an additional 40% is produced in Calabria. The leading provinces in Sicilia are Siracusa, Agrigento and Catania. In Calabria, the most important provinces in the production of oranges are Cosenza, Reggio Calabria, Vibo Valentia, Catanzaro and Crotone. Most of the table grapes production was carried out in Puglia, Sicilia and Basilicata. The provinces most involved in this activity are Taranto, Barletta-Andria-Trani, Bari, Foggia (Puglia), Ragusa, Agrigento (Sicilia), and Matera (Basilicata). Calabria is the leading region in the production of olives. More then 30% of the production of olives in the period come from Calabria. Leading provinces in Calabria are Cosenza, Reggio Calabria and Catanzaro.

These maps show the spatial nature of the agricultural production. The marked geographical distribution of certain agricultural activities are certainlly influenced by local geographic, climatic and economic factors.

In order to compare productive performance of different producing units in agriculture, factors such as biophysical characteristics, regulatory and policy approaches have to be relatively similar (Barnes et al., 2010). If geography is a main driver in the choice the types of products to be produced than, it also influences the technology required to produce that types of products. As we have already discussed for the case of differentials in productivity among different farming types, differences across NUTS3 in relative levels of productivity might be closely linked to the differences in the technical and organizational elements that characterize agricultural specializations. As a consequence, the large productivity differentials observed and the narrow spatial autocorrelation structures of the measurements observed at NUTS3 level might be a reflection of the differences in their agricultural specializations.

As NUTS3 differ in physical environment, a producitvity shock in one location might have a limited spillover effect for the productive performance of neighboring locations because of the differences in technological and organizational endowment. As a consequence, the diffusion of innovation might be a limited and lengthy process in agriculture.

Appendix A

Italian FADN tables

The database provided by CREA[1] contains farm-level information spanning the period 2008-2014. It is composed of the following 25 tables :

Table	Description
FARMS	Contains the general economic and structural information such as ID, location, physical dimension, standard output, LU, AWU, UAA, economic size, specialization
SUBSIDIES	Contains information regarding CAP support received by the farm divided by type of intervention and payment channel
ANIMAL HUSBANDRY	Quantitative physical and financial information regarding livestock by category owned by farms
ENVIRONMENT	Physical and qualitative information regarding natural resources of the farm
LIVESTOCK	Physical and economic characteristics of livestock belonging to the farm or used within the farm y livestock category
INCOME STATEMENT	Statement of revenues and expenses of the accounting period
BALANCE SHEET	Summary of the financial balances
SAMPLE	ID, stratum, weight for each sampled farm
CERTIFICATION	Information on products or processes certifications
CLASSIFICATION	Information on standard output per types of products
CROPS	Economic and physical information about crop productions
LABOR COSTS	Information regarding number of people working on the farm, amount of work supplied to the farm and salary earned by type of workers
BUILDINGS	Physical and economic information regarding farms' buildings
FERTILIZERS	Information regarding value and quantities of fertilizers by type
PESTICIDES	Information regarding value and quantities of pesticides by type
LABOR	Information regarding the characteristics of each of the workers
MACHINES	Information regarding machines and installations used on farm by type and by ownership
MANPOWER	Additional information regarding workers' characteristics
PLANTATIONS	Technical and economic information regarding crops and forest plantations
PRODUCTS	Quantitative and economic information regarding agricultural products produced, purchased, sold, reused, stocked in farm
SERVICES	Physical information regarding services offered such as camping, production of renewable energies, machinery renting, room rent and farmhouse services
LAND	Surfaces and value of land by type of land
SGM TYPOLOGY	Information regarding standard gross margins, economic size and specialization for those companies sampled in 2008 and 2009
WATER USAGE	Information regarding the use of water by crop (volumes, timing)
LAND USE	Land surfaced by type of land use

[1] Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, http://www.crea.gov.it/

The data provided by the Italian FADN and used in this analysis is updated as of 27 July 2016. Values and prices are collected in current values. These values are deflated using appropriate price indexes[2] to transform the current values in 2008-constant values.

[2]Price indexes are taken from the Eurostat Agricultural Price indexes and from other Eurostat data tables.

Appendix B

Sampled farms

The Italian FADN is the Italian subset of the FADN. The FAND is a EU tool for evaluating the income of agricultural holdings and the impacts of the CAP. It does so by collecting information on a sample of farms throughout the EU every year. The sampling strategy and data collection are made by the Liaison Agencies in each EU Member State under certain general guidelines and with the approval of the EU Commission. In Italy, the Liaison Agency is the CREA[1].

The FADN field of observation consists of the subset of the universe of the Farm Structure Survey[2] named commercial farms. Commercial Farms are defined as farms large enough to provide a main activity for the farmer and a level of income sufficient to support his or her own family. To be classified as such a farm need to exceed a minimum economic size and the thresholds for the minimum size are established at the level of Member States.

In Italy, until 2009 the minimum economic size to be classified as commercial farm was 4 UDE. A UDE is a measure of economic size and corresponds to 1200 EUR of Standard Gross Margin. The standard gross margin of a crop or livestock item is defined as the value of output from one hectare or from one animal less the cost of variable inputs required to produce that output. The economic size of a farm was obtained by summing up all the SGMs for all crop or livestock product.

Since 2010, the minimum economic size to be classified commercial in Italy was a Standard Output (SO) larger than 4000 EUR. THE SO is the monetary of the gross agricultural output at the farm-gate price. It is obtained for each farm by multiplying the Standard Output per unit of crop and

[1] Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria

[2] The universe of the FSS is composed of all agricultural holdings in the EU of at least 1 hectare and those of less than 1 hectare provided the latter market a certain proportion of their output or produce more than a specified amount of output

livestock product by the corresponding number of units of crop and livestock products. Standard Outputs per unit of product is an average monetary measure per unit that is calculated for each crop and livestock product over a period of five years in each region.

The Italian FADN samples in Italy around 11,000 agricultural holdings annually. The sample size of the Italian FADN is one of the largest in the EU (Hansen et al., 2009). Each year CREA draws a random sample stratified along the dimension of FADN region, economic size and types of farming. A constant subsample is also added to the random sample.

Representativeness of the FADN sample with respect to the actual universe of commercial farm, as listed by the FSS, might be undermined by the inclusion of two additional sample selection criteria. To be included into the sampling frame, agricultural holdings must: have a suitable set of farm accounts and be willing to participate. As a result, the sample is actually drawn at random from the subset of commercial farms that fulfill these two criteria.

After the sampling is done a weight is attached to each sample. The weight corresponds to the number of agricultural holdings that the sampled one represents. According to the sampling plan, if a stratum is composed of 100 farms and only 20 of them are sampled, than each of the sampled farm will have a weight equal to 5 ($100/20 = 5$).

The purpose of the weighting procedure is to derive an approximation of the population's values by using information on a much smaller number of agricultural holdings. Thus, it is likely that the higher the weight the less reliablethe inferential procedure is because it is assumed that the represented farms are equal in terms of activities and structure to the sampled one.

Country level

At the most aggregate level, around 11,000 farms are sampled annually by CREA. The highest number of sampled farms is registered in 2008 and 2013 with more than 11,330 farms. The year in which the smallest number of sampled farms is recorded is the latest year, the 2014 with less than 10,500 farms.

By summing up the weights attached to each farms is possible to derive the number of farms that are represented by the sampled ones. The temporal distribution of the represented farms is presented in the third column of Table B.1. It is possible to see that, although the number of sampled farms stayed relatively constant throughout the period 2008-2013, the number of represented farms has slightly increased over time. This is reflected also in the increasing average weight that is applied to each farm at national level.

Year	Sample	Universe	Average weight
2008	11,389	693,649	60.9
2009	11,029	693,617	62.9
2010	11,155	785,920	70.5
2011	11,237	779,657	69.4
2012	11,178	792,627	70.9
2013	11,319	800,844	70.8
2014	10,487	596,215	56.9

Table B.1: Sampled farms, represented farms and average weights, national level

It is possible to see that the average weight has increased from 60.9 in 2008 to 70.8 in 2013. The 2014 marks a break in the trend with a drastic fall in the number of sampled farms and in the number of represented farms. But their relative difference is also decreased as reflected by the decrease in the average weight to 56.9. It might be inferred by the decrease in the average weight that the representativeness of the sampling strategy increased in 2014 after a period of decreasing reliability.

It is also possible to compare the estimates with the number of holdings as provided by the FSS in 2010 and in 2013[3]. In terms of the number of agricultural holdings in Italy exceeding the minimum economic size of 4000 EUR, the FSS recorded 838,740 and 711,820 holdings in 2010 and in 2013 respectively. In the same years, the number of represented farms in the Italian FADN database is 785,920 and 800,844 respectively. The FADN data do not seem to align with the trends recorded by the FSS. In fact, the number of holdings, as recorded by the FSS, diminished considerably between 2010 and 2013 while, according to the FADN data, the number of represented commercial farms has slightly increased over the period.

Another interesting feature of the sample regards how the composition of the sample has changed over time. In particular, since farm-level data with weights attached are used to approximate aggregate data and to derive output and input indexes at an aggregate level, it is interesting to see how the composition of companies within each aggregate has changed. This might help in interpreting the output and input indexes derived. In fact, it could be assumed that a higher turnover rate of companies is associated with a

[3] The FSS data collection was carried most recently in 2005, 2007, 2010 and 2013.

higher volatility of aggregate indexes.

Figure B.1 shows the time-series of the turnover of sampled companies year-to-year (pink line) and year-to-period (blue line) . The year-to-year turnover is the share of companies that in each year are newly sampled with respect to the previous year. The year-to-period turnover is the percentage of companies that have entered the sample for the first time since 2008.

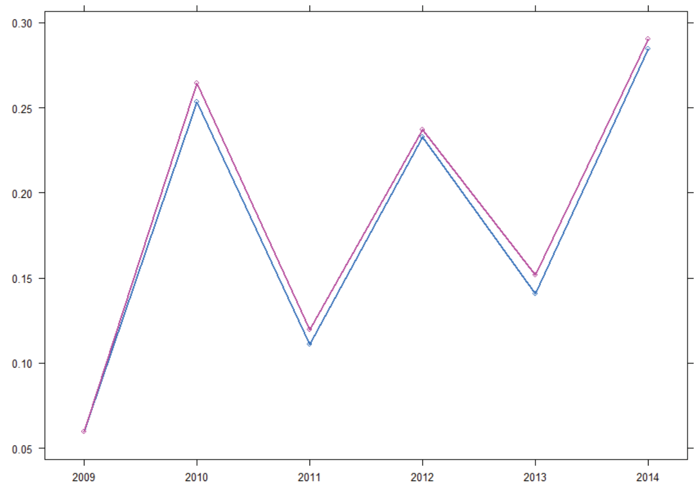

Figure B.1: Turnover rates, national level

The two curves are close together meaning that, typically, the new companies surveyed every year are new to the whole dataset. The second pattern that is easily identifiable is the average number of new companies in each year that stands around 18%. This means that, on average, 18% of the companies that are surveyed annually are new companies.

Another interesting feature is that the turnover rate changed drastically from year to year. In 2010, 2012 and 2014 the turnover rate stood high at around 25% while in 2009, 2011 and 2013 the turnover rate was relatively low at between 6% and 15%.

FADN regions

The FADN sample is stratified along the dimensions of FADN region, economic size and type of farming. The FADN regions in Italy are 21 and corresponds almost entirely to the NUTS2 administrative division. The only exception is given by Trentino-Alto Adige that in the FADN map is split into two regions, i.e., Trentino and Alto Adige.

Among the 21 FADN regions the most sampled are Piemonte, Emilia Romagna, Veneto, Toscana and Lombardia with an average annual number of sample companies of respectively 1029, 916, 733, 665 and 628 holdings. On average they represent the 9.2%, the 8.2%, the 6.5%, the 5.9% and the 5.6% of the agricultural holdings sampled annually in Italy. The number of sampled farms in Emilia Romagna and Toscana has been steadily declining throughout the period.

The least sampled regions are Valle d'Aosta, Trentino and Molise with respectively an average number of sampled companies of per year of 183, 279 and 335 farms accounting for the 1.6%, 2.5% and 3% of the companies sampled annually in Italy.

By applying the weight to each of the sampled farm and aggregating that number at the level of FADN region, it is possible to derive the geographical distribution of represented farms over time.

The number of sampled and represented farms by FADN region is presented in Table B.2. The share of sampled and represented farms by FADN region is presented in Table B.3. Regarding the number of represented farms, the story is somewhat different with respect to the sampled ones. There are FADN regions that represent a large number of companies while the number of their sampled companies are relatively small. It is interesting to inspect these trends because they might help in understanding the reliability of the estimates.

First of all, it is possible to notice that a number of regions have a relatively high share of represented farms each year. The number of regions with the highest average share are respectively Puglia, Sicilia, Campania, Veneto and Emilia Romagna. Secondly, among these regions the ones that have a large number of sampled farms are only Emilia Romagna and Veneto. The others, all coming from the Southern part of the country, have a relatively low number of sampled companies. The discrepancy between the number of sampled and represented farms becomes clear by looking at the time-series of the average weight by FADN region in Figure B.2. It is clear that Puglia, Sicilia, Campania but also Calabria have a very high average weight attached to each farms. The weight for these regions is higher than 100 or even 150 while the average for the whole sample is around 63.

The fact that some regions are associated with a high average weight could be attributed to two possible sources: a high degree of homogeneity of farms in the regions or to a lower degree of reliability of the sampling plan. If the second hypothesis were supported, then one should be more cautious in interpreting the corresponding estimates.

In terms of turnover rate, the year-to-year and year-to-period turnover curves are very close together as in the aggregate case. This mens that

FADN	2008		2009		2010		2011		2012		2013		2014	
region	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.
AB	523	24,402	508	24,318	441	27,200	439	27,049	431	20,876	445	20,859	526	20,986
AA	337	14,205	349	14,023	213	16,684	261	16,980	261	15,831	262	15,864	325	14,150
BA	449	19,031	420	19,063	420	19,570	405	19,517	388	18,310	420	19,170	360	13,804
CL	348	37,878	315	40,075	470	67,689	474	68,197	471	68,057	466	67,730	461	41,427
CM	441	55,972	441	55,378	593	65,443	574	65,019	582	65,371	598	64,750	587	43,451
ER	1,168	58,363	1,055	59,084	1,011	58,874	878	57,623	845	58,297	760	59,286	701	48,828
FV	652	11,672	632	11,619	510	11,669	519	11,255	516	11,995	520	11,945	389	8,506
LA	449	33,186	445	33,907	500	43,116	557	42,755	524	42,312	577	42,780	709	30,508
LI	473	10,305	472	10,122	519	9,449	512	9,435	559	9,094	559	9,082	399	6,726
LO	648	38,112	597	38,176	639	37,729	611	36,809	640	38,091	630	38,449	634	33,281
MA	530	22,551	552	22,786	447	21,739	475	21,685	481	21,641	456	21,869	379	15,181
MO	322	8,372	319	7,953	338	9,758	348	9,891	348	9,560	351	9,608	323	6,534
PI	1,005	44,919	1,037	45,912	1,054	49,993	1,032	49,528	1,031	51,104	1,037	50,788	1,008	41,714
PU	452	91,418	449	91,357	682	89,909	721	89,867	683	90,180	674	95,327	611	62,551
SA	371	27,676	377	26,005	524	33,858	522	34,767	537	34,894	708	34,893	510	29,073
SI	457	76,814	450	75,669	598	98,532	641	96,544	628	108,747	651	108,505	617	80,800
TO	867	35,082	817	35,190	626	35,642	630	35,192	620	35,066	608	37,971	488	27,658
TR	322	10,069	307	9,978	256	11,826	279	10,569	263	10,687	279	11,822	248	9,814
UM	436	9,754	454	9,826	465	15,047	495	15,192	473	15,824	468	15,756	426	9,964
VA	260	1,275	194	1,389	158	1,796	156	1,761	190	1,826	159	1,655	168	1,254
VE	879	62,593	839	61,789	691	60,398	708	60,024	707	64,863	691	62,734	618	50,006

Table B.2: Sampled (sam.) and represented farms (uni.) by FADN region

FADN	2008		2009		2010		2011		2012		2013		2014	
region	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.
AB	0.046	0.035	0.046	0.035	0.040	0.035	0.039	0.035	0.039	0.026	0.039	0.026	0.050	0.035
AA	0.030	0.020	0.032	0.020	0.019	0.021	0.023	0.022	0.023	0.020	0.023	0.020	0.031	0.024
BA	0.039	0.027	0.038	0.027	0.038	0.025	0.036	0.025	0.035	0.023	0.037	0.024	0.034	0.023
CL	0.031	0.055	0.029	0.058	0.042	0.086	0.042	0.087	0.042	0.086	0.041	0.085	0.044	0.069
CM	0.039	0.081	0.040	0.080	0.053	0.083	0.051	0.083	0.052	0.082	0.053	0.081	0.056	0.073
ER	0.103	0.084	0.096	0.085	0.091	0.075	0.078	0.074	0.076	0.074	0.067	0.074	0.067	0.082
FV	0.057	0.017	0.057	0.017	0.046	0.015	0.046	0.014	0.046	0.015	0.046	0.015	0.037	0.014
LA	0.039	0.048	0.040	0.049	0.045	0.055	0.050	0.055	0.047	0.053	0.051	0.053	0.068	0.051
LI	0.042	0.015	0.043	0.015	0.047	0.012	0.046	0.012	0.050	0.011	0.049	0.011	0.038	0.011
LO	0.057	0.055	0.054	0.055	0.057	0.048	0.054	0.047	0.057	0.048	0.056	0.048	0.060	0.056
MA	0.047	0.033	0.050	0.033	0.040	0.028	0.042	0.028	0.043	0.027	0.040	0.027	0.036	0.025
MO	0.028	0.012	0.029	0.011	0.030	0.012	0.031	0.013	0.031	0.012	0.031	0.012	0.031	0.011
PI	0.088	0.065	0.094	0.066	0.094	0.064	0.092	0.064	0.092	0.064	0.092	0.063	0.096	0.070
PU	0.040	0.132	0.041	0.132	0.061	0.114	0.064	0.115	0.061	0.114	0.060	0.119	0.058	0.105
SA	0.033	0.040	0.034	0.037	0.047	0.043	0.046	0.045	0.048	0.044	0.063	0.044	0.049	0.049
SI	0.040	0.111	0.041	0.109	0.054	0.125	0.057	0.124	0.056	0.137	0.058	0.135	0.059	0.136
TO	0.076	0.051	0.074	0.051	0.056	0.045	0.056	0.045	0.055	0.044	0.054	0.047	0.047	0.046
TR	0.028	0.015	0.028	0.014	0.023	0.015	0.025	0.014	0.024	0.013	0.025	0.015	0.024	0.016
UM	0.038	0.014	0.041	0.014	0.042	0.019	0.044	0.019	0.042	0.020	0.041	0.020	0.041	0.017
VA	0.023	0.002	0.018	0.002	0.014	0.002	0.014	0.002	0.017	0.002	0.014	0.002	0.016	0.002
VE	0.077	0.090	0.076	0.089	0.062	0.077	0.063	0.077	0.063	0.082	0.061	0.078	0.059	0.084

Table B.3: Annual share of sampled and represented farms by FADN region

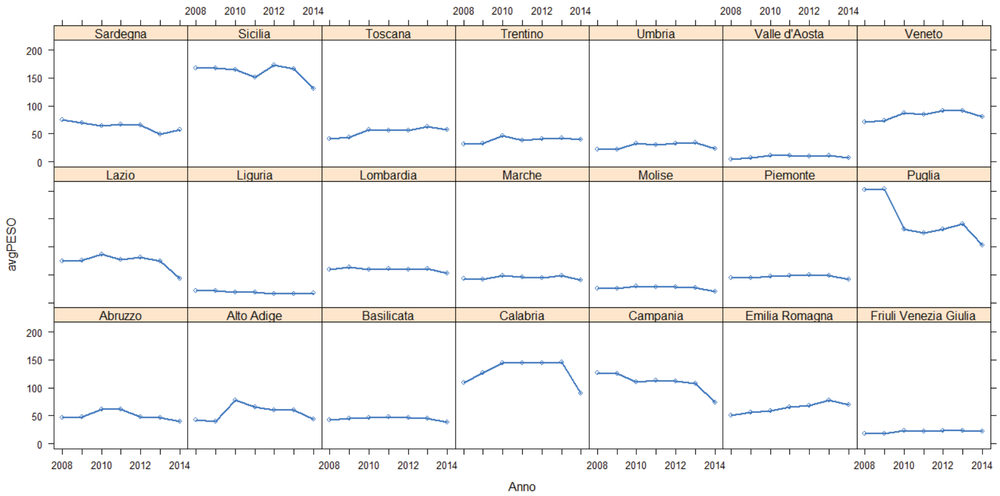

Figure B.2: Average weight by FADN region

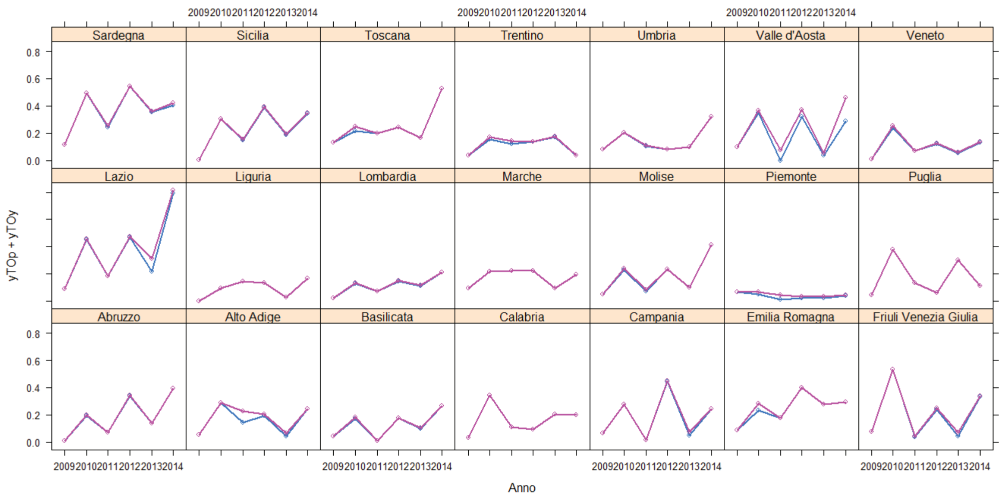

Figure B.3: Turnover rates by FADN region the companies that are newly sampled in each of the year have never been sampled before and this applies to all regions. The only exceptions are Alto Adige in 2011 and Lazio in 2013. In these two regions, the gap between the year-to-year and the year-to-period curve is larger than for the rest of the regions. For what regards the average level of turnover, some regions share a higher average turnover rate with respect to the others. The average year-to-year turnover is very high for Sardegna and Lazio. These two regions have an average annual turnover rate of above 30%. At regional level, the average yearly turnover rate stands at 18.9%. Some regions perform fairly better with respect to the average. In particular, Piemonte and Liguria have an average yearly turnover rate below 10%. The expected implications for the rate of turnover are that one would expect the indexes of output and inputs be more stable for regions under more stable sampling conditions and be more volatile in the case of a higher turnover rate due to the quasi-random nature of the FADN sample.

NUTS3

NUTS3 corresponds perfectly with the Italian administrative division of provinces in 2011. Collectively, there are 110 provinces in the FADN database. However, in the present analysis three NUTS3 were merged with other neighboring ones in order to be able to derive specific indexes for inputs such as fertilizers and pesticides. Some of the provinces, due to the very low number of sampled companies in some of the years did not have information on some of the most important inputs. Therefore, it was decided to aggregate them into larger spatial units. The spatial aggregation was made while meeting the largest number of the following criteria:

- NUTS3 must be merged with other NUTS3 belonging to the same NUTS2;
- NUTS3 must be merged with neighboring ones who share the lowest possible number of sampled companies;
- the final geographical combination of the two merged provinces ought to be latitudinally and longitudinally restricted.

Following this procedure, Varese was merged with Como, Monza e delle brianza with Lecco and Verbano-Cusio-Ossola with Novara. Figure B.4 gives a geographical representation of the aggregation procedure. The final number of NUTS3 in the analysis is 107.

There is high variability in the number of sampled companies per NUTS3. Those that have a higher relative share of sampled companies in each of

Figure B.4: Spatial aggregation of selected NUTS3

the year of the period 2008-2014 are Perugia (Umbria), Cuneo (Piemonte), Campobasso (Molise), Udine (Friuli Venezia Giulia), Bolzano (Alto Adige), Trento (Trentino), Imperia (Liguria) and Verona (Veneto). These NUTS3 have an annual average share of sampled companies that is above the 2% of the entire sample in each year. The least sampled NUTS3 are Monza e della Brianza, Lecco, Verbano-Cusio-Ossola that have from two to four companies sampled annually in some of the years. They are thus merged with neighboring NUTS3.

Summing the weights applied to each farm and aggregating at NUTS3 level it is possible to derive the number of represented farms by province. Under the hypothesis that the represented farms lie within the province boundaries of their representative farm, the number of represented farms provides an approximate value to the total values at NUTS3 level. The annual share of represented farms by NUTS3 is depicted in the map in Figure B.5.

From the maps it is easy to see that the highest share of represented farms are located into provinces in the North-East, in the Central-West, and in the South. For what regards the provinces in the North-East and in the Central-West, the high number of represented farms is matched with a high number of sampled companies. This is not true for many Southern provinces. For many of them, sampled companies have a very high number of represented farms. This is reflected by the high average weight throughout the years in the Southern part of the country. The map of average weight by NUTS3 is presented in Figure B.6. As noted earlier, two possible explanations for a higher weight can be the fact that there is high homogeneity of farming

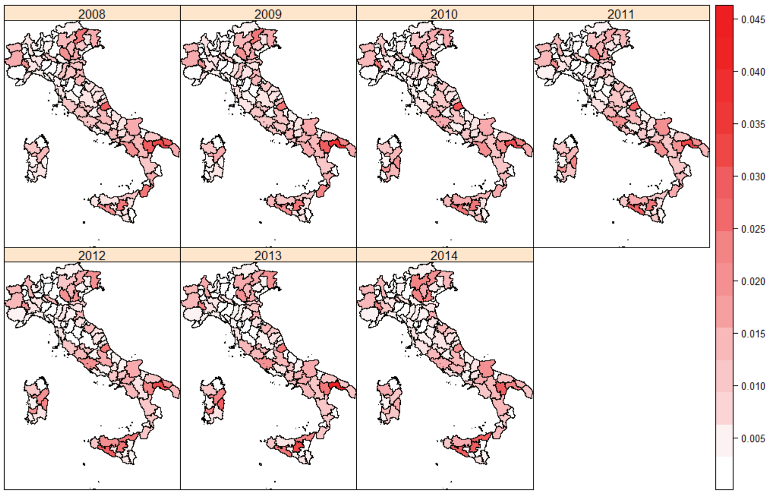

Figure B.5: Annual share of represented farms by NUTS3

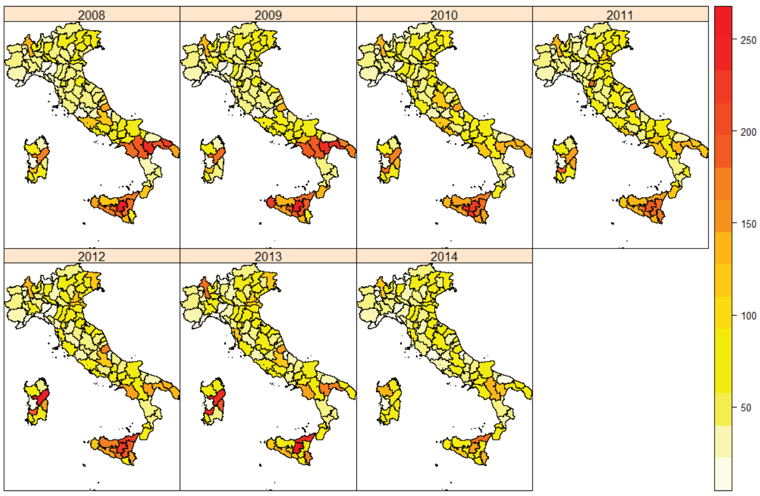

Figure B.6: Average weight by NUTS3

structures or because the approximation involved is larger. In this second case, we should be cautious in interpreting the productivity statistics from those NUTS3.

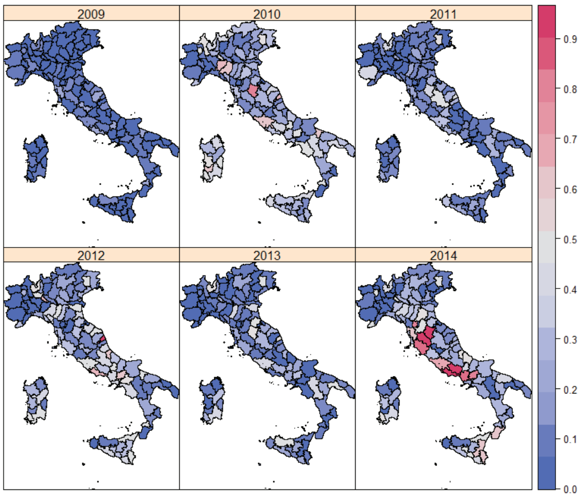

Figure B.7: Turnover rate by NUTS3

The year-to-year turnover rate was very low in 2008 and very high in 2010, 2012, and in 2014 as in the aggregate data. For some NUTS3, the turnover was particularly high in these years. A year-to-year turnover higher than 80% was found in the provinces of Livorno, Roma, Pisa Rieti, Arezzo, Latina, Frosinone e Massa-Carrara in 2014 and in Ogliastra in 2012. The map of the year-to-year turnover rate in presented in Figure B.7.

Types of farming

The types of farming provided in the Italian FADN are the following ten classes: dairy, cereals, grazing livestock, fruits, granivores, mixed crops and livestock, olives, horticulture, arable crops and wine. The link between the code for the types of farming and the classes provided in the Italian FADN is presented in Appendix F. The distribution of the sampled and represented farms by type of farming is provided in Table B.4.

All types of farming have a high number of sampled companies. The least sampled class is the granivores with around 400 sampled farms annually. By applying the weights to the corresponding farms and aggregating by class, it is possible to derive the distribution of represented farms. These are presented for each year in the column "univ.". This distribution represents the

Types of farming	2008		2009		2010		2011		2012		2013		2014	
	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.
Dairy	1,325	49,063	1,170	48,283	1,083	34,886	1,064	33,721	1,068	33,180	1,102	33,683	937	31,317
Cereals	1,622	123,610	1,429	121,698	1,367	104,432	1,375	102,860	1,341	103,728	1,296	101,835	1,134	61,100
Grazing livestock	1,092	40,038	1,154	39,915	1,372	70,595	1,392	69,442	1,505	72,682	1,693	71,555	1,507	68,104
Fruits	1,834	132,050	1,830	133,622	1,382	146,220	1,446	146,242	1,247	154,494	1,249	155,150	1,328	92,228
Granivores	323	5,368	285	4,776	424	7,468	408	7,263	517	7,152	507	7,518	492	7,967
Mixed	822	40,502	826	43,699	952	76,950	990	77,152	987	75,510	991	77,267	968	48,737
Olives	466	80,716	458	81,145	468	74,351	499	74,711	479	73,640	480	72,578	432	41,518
Horticulture	1,173	56,455	1,154	54,167	1,482	62,778	1,448	63,697	1,495	61,811	1,464	62,698	1,225	61,207
Arable crops	1,638	104,311	1,673	101,781	1,172	77,893	1,153	79,170	1,194	76,181	1,246	78,209	1,216	60,388
Wine	1,094	61,535	1,050	64,533	1,453	130,348	1,462	125,399	1,345	134,249	1,291	140,351	1,248	123,649

Table B.4: Sampled and represented farms, types of farming

distribution of commercial farms in Italy by specialization. It is worth noticing that there is a considerable difference between the number of sampled farms and the number of represented ones for some specialization. Olives, fruits, wine, mixed and cereals, especially in some years, have a number of sampled farms that is small with respect to the number of represented farms relative to other classes.

Types of farming	2008		2009		2010		2011		2012		2013		2014	
	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.
Dairy	0.116	0.071	0.106	0.070	0.097	0.044	0.095	0.043	0.096	0.042	0.097	0.042	0.089	0.053
Cereals	0.142	0.178	0.130	0.175	0.123	0.133	0.122	0.132	0.120	0.131	0.114	0.127	0.108	0.102
Grazing livestock	0.096	0.058	0.105	0.058	0.123	0.090	0.124	0.089	0.135	0.092	0.150	0.089	0.144	0.114
Fruits	0.161	0.190	0.166	0.193	0.124	0.186	0.129	0.188	0.112	0.195	0.110	0.194	0.127	0.155
Granivores	0.028	0.008	0.026	0.007	0.038	0.010	0.036	0.009	0.046	0.009	0.045	0.009	0.047	0.013
Mixed	0.072	0.058	0.075	0.063	0.085	0.098	0.088	0.099	0.088	0.095	0.088	0.096	0.092	0.082
Olives	0.041	0.116	0.042	0.117	0.042	0.095	0.044	0.096	0.043	0.093	0.042	0.091	0.041	0.070
Horticulture	0.103	0.081	0.105	0.078	0.133	0.080	0.129	0.082	0.134	0.078	0.129	0.078	0.117	0.103
Arable crops	0.144	0.150	0.152	0.147	0.105	0.099	0.103	0.102	0.107	0.096	0.110	0.098	0.116	0.101
Wine	0.096	0.089	0.095	0.093	0.130	0.166	0.130	0.161	0.120	0.169	0.114	0.175	0.119	0.207

Table B.5: Share of sampled and represented farms, types of farming

The gap between the number of sampled companies and the number of represented companies is summarized in the time-series of the average weight by types of farming. It is possible to see that olives and fruits have a very high average weight attached to each of their farms. Also wine, cereals and mixed are associated with average high weights but just in some of the years. In addition, it seems that there exists a break in the series between the period 2008-2009 and the period 2010-2014. It seems as if, for most specialization, the share of companies have changed in line with the change in the data collection done between these two periods (in 2010). Two possible explanations for this change are i) the change in the data collection and, in particular, the update of the unit SO coefficients associated with each agricultural product

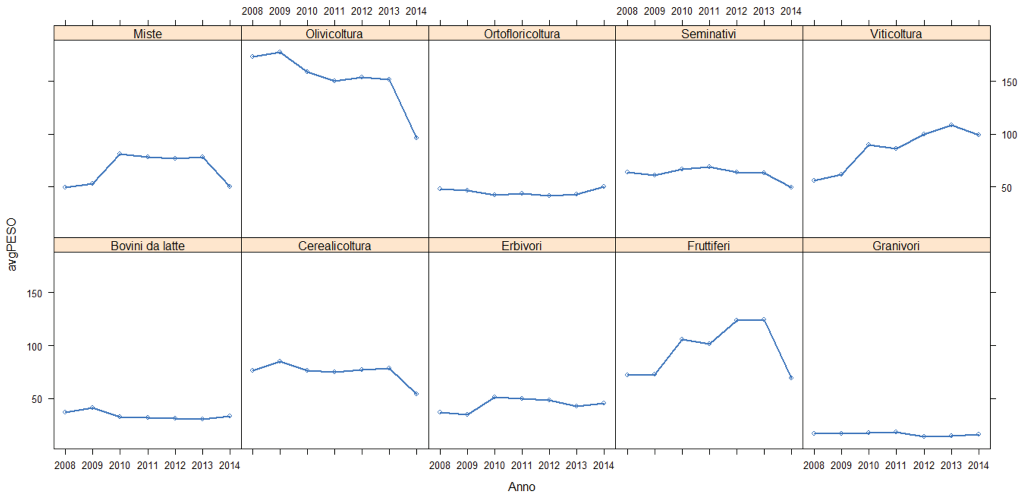

Figure B.8: Average weights, types of farming

has led to a different classification of the companies ii) the actual composition of the Italian commercial agriculture has changed between these two periods.

In terms of turnover, some specializations have an higher turnover rate with respect to the others. In particular, Mixed have a remarkably high rate of turnover. Also arable crops and grazing livestock share a high average level of turnover. Another interesting feature that can be detected from these time-series is that it appears as if there are two types of trends shared by the groups: one in which the rate of turnover is relatively high in 2010, 2012 and 2014 and another one in which the rate of turnover is high in 2010 and 2014 but not in 2012. Olives, cereals and fruits belong to this second group. It is also worth noticing how the year-to-year turnover is different to the year-to-period turnover for some specializations. Mixed, arable crops, and cereals seem to have a wider gap between the two curves and ths meas that, in each year, the number of new companies entering the dataset are companies that have been surveyed in some of the previous periods.

Size classes

The size of agricultural holdings is determined by their economics size. The classification of economic sizes of farms used in this analysis is provided in the Italian FADN database. This classification attempted to harmonize the differences in the European classifications between the two data collection periods: 2008-2009 and 2010-2014. This classification is a function of the

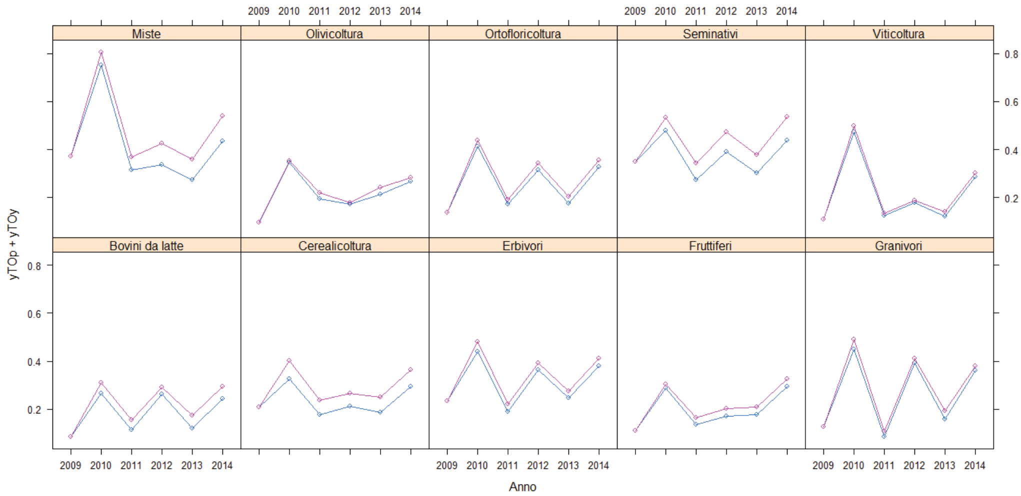

Figure B.9: Turnover rates by types of farming

Standard Output of agricultural holdings. However, because of the change in the methodology with which the Standard Output has been measured in the two sub-periods, also the size classes have a high number of companies moving from one class to the other even though the farms ave not changed their structure at all. In order to reduce the bias produced by the change in the classification, in the present analysis a specific procedure has been undertaken in order to increase the comparability between the two data collection periods.

In particular, for the period 2008-2009 the SO unit coefficients have been replaced (when possible) with the SO unit coefficients of the period 2010-2014. In a second stage, the SO per agricultural product have been aggregated by farm in each of the accounting year. The recalculated SO is then used to classify the farms in three class size according to the pre-defined thresholds[4]. Details of the procedure are presented in Annex G.

The resulting distribution appears to be more balanced than the previous one. The class that on average is most sampled is the class of the medium-sized farms with around 4,500 farms sampled annually. The class that follows is the class of large farms with around 3,500 farms sampled annually. The remaining class is the one with the small-sized ones and it is composed annually on average by 3,000 companies.

Given the distribution of the sampled farms, it is clear how much the Italian FADN sample is unbalanced in favor of the large farms. By looking

[4]A farm is small is its SO is less than 25,00 EUR; it is considered medium-sized when the SO is between 25,001 and 50,000; it considered large when its SO is larger than 100,000.

at the number of represented farm, this is even clearer. The represented farms should represent the actual distribution of the companies by size and by year. On average, it seems as the small farms account for around the 60% of the total number of companies while in the present database the share of small size sampled companies is considerably less than the 30% share. The medium-sized farms represent on average around the 30% share of the sampled companies and the average share of the sampling plan give is about the same. In contrast, large farms are largely overrepresented. While they should account for around the 10% of the sampled companies, in fact, they account for around the 40% of the sampled ones.

Size	2008		2009		2010		2011		2012		2013		2014	
classes	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.
Large	3, 628	65, 256	3, 537	67, 397	3, 662	85, 742	3, 604	85, 535	3, 725	85, 931	3, 728	86, 056	3, 402	86, 918
Medium	4, 613	210, 980	4, 525	215, 858	4, 352	215, 019	4, 488	214, 225	4, 356	214, 964	4, 548	215, 632	4, 512	215, 959
Small	3, 148	417, 414	2, 967	410, 362	3, 141	485, 159	3, 145	479, 897	3, 097	491, 732	3, 043	499, 156	2, 573	293, 338

Table B.6: Sampled and represented farms by class size

Size	2008		2009		2010		2011		2012		2013		2014	
classes	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.	sam.	uni.
Large	0.319	0.094	0.321	0.097	0.328	0.109	0.321	0.110	0.333	0.108	0.329	0.107	0.324	0.146
Medium	0.405	0.304	0.410	0.311	0.390	0.274	0.399	0.275	0.390	0.271	0.402	0.269	0.430	0.362
Small	0.276	0.602	0.269	0.592	0.282	0.617	0.280	0.616	0.277	0.620	0.269	0.623	0.245	0.492

Table B.7: Share of sampled and represented farms by class size

Average weights by size classes is presented in Figure B.10. On average, the large farms sampled represent around 20 represented farms. Medium-sized farms are associated with a weight that is around the double of the weight for large farms while small farms are associated with a much larger average weight. On average, each sampled farm classified as small represents around 150 small farms.

The turnover rates are presented in Figure B.11. Rates are similar across size classes. For small farms, turnover rates appear to be sightly higher than the other classes. Particularly high was the turnover rate in 2010, 2012 and 2014 for all size classes.

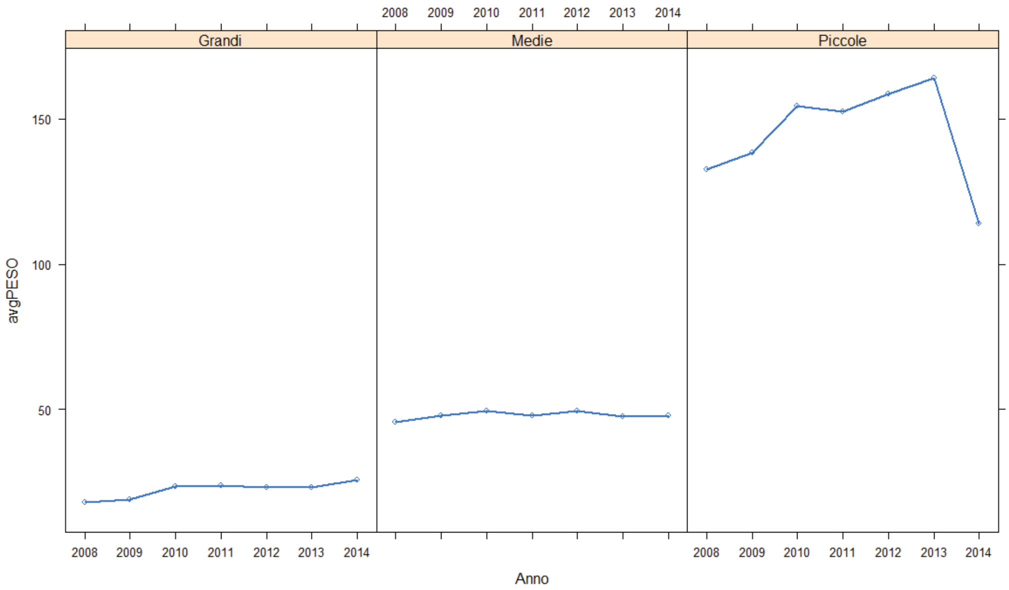

Figure B.10: Average weight by class size

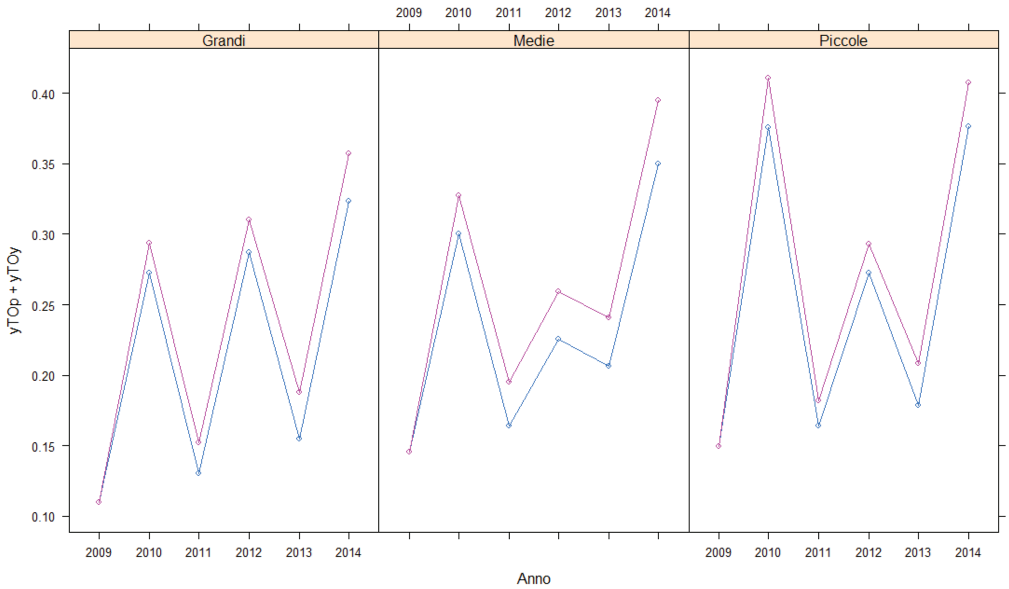

Figure B.11: Turnover rates by class size

Appendix C

Derivation of the output index

Exclusion of products with large variations

The output index is created from the information contained in the table PRODUCTS. This table contains detailed information on the quantity and values of 1047 products. As some of them exhibit huge year to year variations in the quantity produced, in this analysis we decided to exclude them from the computation of the output index. The reason why they were excluded is because huge year to year variations in quantities might cause large fluctuations in the output index and biases in the derivation of the productivity indexes. Huge year to year fluctuations might be due to errors in the data collection methodology and to different units of measurements rather than due to an actual change in production quantities. As the index number procedure does not take into account the presence of noise in the data, the present analysis excludes the products that might drive large fluctuation in aggregate indexes.

The products that were excluded from the analysis were those that exhibited a year to year variations larger than 10,000% in, at least, one of the year of the panel. There are 29 products that exhibit such year to year variations in the quantity produced. They are the following:

- alcool di Vite per vino comune
- Altri prodotti di Suini
- Altri prodotti lattiero caseari di Ovini
- altri prodotti olive di Olivo per olive da olio
- altri sottoprodotti di Altre ortive
- altri sottoprodotti di Altre piante aromatiche, officinali e medicinali
- altri sottoprodotti di Porro
- Carni fresche e congelate di Tacchini
- erba verde di Erbaio di altre specie

– erba verde di Erbaio di leguminose
– erba verde di Erbaio di sorgo in erba e a maturaz cerosa
– erba verde di Erbaio di Sorgo zuccherino
– fieno di Erbaio di Sorgo zuccherino
– marmellata di frutta di Lampone
– marmellata di frutta di Melo
– marmellata di frutta di Mora di rovo
– marmellata di frutta di Susino
– piante di Begonia
– piante di Rose
– piante e fiori per essenze e aromi di Altre piante aromatiche, officinali e medicinali
– piante e fiori per essenze e aromi di Aneto
– piante e fiori per essenze e aromi di Camomilla
– piante e fiori per essenze e aromi di Lavanda
– piante e fiori per essenze e aromi di Menta
– prodotti del vivaio di Vivaio piante aromatiche, medicinali e officinali
– residui della potatura di Vite per vino DOC e DOCG
– sidro di Melo
– Siero di Bovini
– tuberi di bieta da radice

Collectively, they contribute to a small share of the total production for every year. Their total contributions ranges between 0.42% in 2008 to 0.065% in 2012. Their contribution is small and relatively stable over time so that the time-series of aggregate indexes should not be affected by their exclusion.

Year	**Value share**
2008	0.00370
2009	0.00425
2010	0.00197
2011	0.00136
2012	0.00065
2013	0.00099
2014	0.00158

Table C.1: Annual value share of excluded products

Macro-categories used in the products aggregation step

To make the panel output comparisons more meaningful, a product aggregation procedure has been used. In this procedure, a number of products with similar features were merged together. The products selected to be aggregated were the products that were not included in the definition of *major* products considered in Appendix D. These non-major products were aggregated into 56 macro-categories taking into account their characteristics and unit of measurement.

The macro-categories used in the aggregation procedure are the following:

- aceto HL
- acquavite LT
- alcool LT
- carni QL
- formaggio QL
- altri prodotti frutta KG
- altri prodotti viticoltura QL
- altri prodotti olivicoltura QL
- altri prodotti erbacee QL
- altri prodotti ortive QL
- altri prodotti piante industriali QL
- altri prodotti cereali QL
- altri prodotti piante QL
- altri prodotti legumi QL
- altri prodotti animali MG
- ortaggi QL
- latte QL
- prodotti apicoltura QL
- erba verde QL
- essenze KG
- farina QL
- fibre tessili QL
- fieno QL
- fieno UB
- fiori CTS
- fronde QL
- frutta lavorata QL
- frutta QL
- legumi QL
- piante industriali QL
- cereali QL

- insilato QL
- lana QL
- legno MC
- legno QL
- letame QL
- marmellata KG
- mosto HL
- olio QL
- paglia QL
- pascolo QL
- pascolo UB
- altri prodotti animali QL
- piante CTV
- piante per essenze e aromi MG
- cereali lavorati QL
- salumi QL
- residui potatura QL
- segatura e trucioli MC
- semi foraggere MG
- semi foraggere QL
- semi piante tessili QL
- succhi di frutta LT
- uova MG
- vinacce QL
- vino HL

Minimum spanning trees of the output indexes

In this section the minimum spanning trees used in the construction of the chained output indexes at the level of FADN regions, types of farming, and size classes are presented.

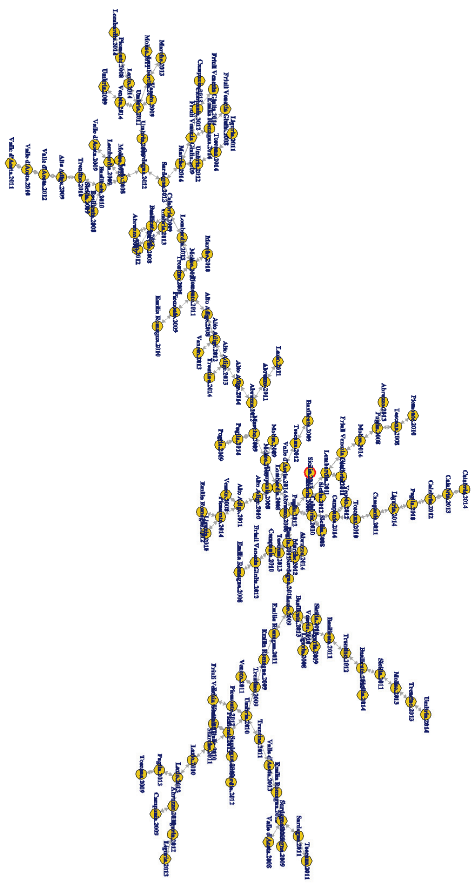

Figure C.1: MST output index, FADN regions

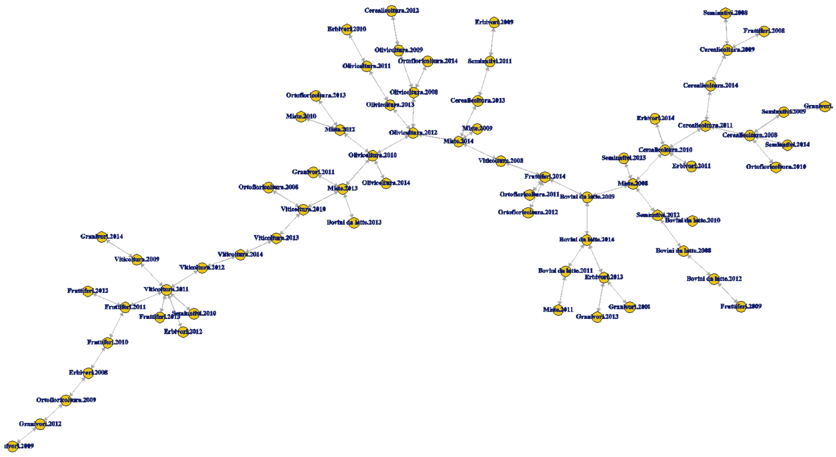

Figure C.2: MST output index, types of farming

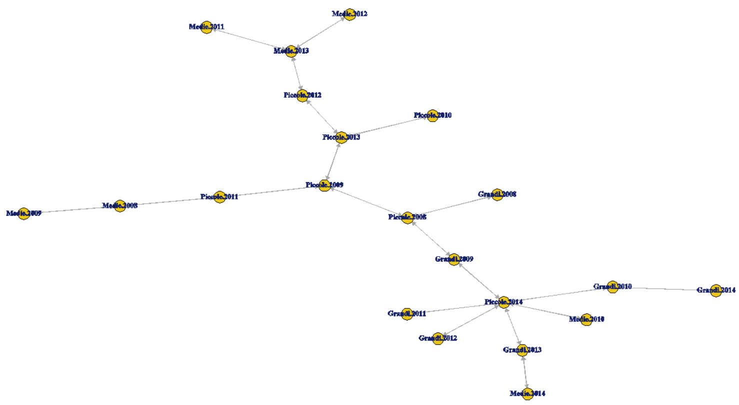

Figure C.3: MST output index, size classes

Appendix D

Selection of the products aggregation procedures

The output indexes for the different levels of analysis are created after a specific products aggregation procedures. As the number of available products is very large, the aggregation procedure should help creating more meaningful output comparisons between spatial units and, at the same time, save computation time.

The aggregation procedure consists in two steps: first, the products that make for a certain share of the production value of each region in every year are selected[1], and secondly, the remaining products are aggregated into 56 macro-categories. The main challenge at this point is to select the relevant share of the regional production values. This share will separate the group of products that will be aggregated from those that will not. We will conveniently name the products that will not be aggregated as the *major products*.

The specific share changes for each analysis so that each output index is the one that is based on the most reliable binary comparisons. Every time, the selection is done in two steps. In the first step, the output index is calculated using different share values[2]. Second, the best share value is selected based on the most reliable of the computed output indexes. The reliability of the output index is defined as the sum of the Paasche-Laspeyres Spreads (PLS) across the minimum spanning tree associated with the index. The lower the sum, the more reliable the output index.

[1] An additional criterion to be simultaneously satisfied is that for every region a number of at least 8 products must be selected before the algorithm stops. The share value is augmented with an additional 1% share at every iteration until the two conditions are satisfied together.

[2] The different values tried out are included in the interval between 20% and 95% considering a step of 2.5%.

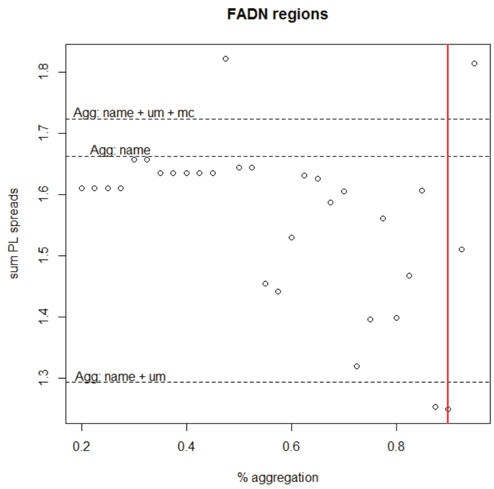

Figure D.1: PLS sums, FADN regions

The reliability of the output indexes is evaluated also without the products aggregation step. It is computed also for output indexes that differentiate products based on their name only (Agg: name), based on their name and on their corresponding unit of measurement (Agg: name + um) and based on their name, their unit of measurement and their method of cultivation (Agg: name + um + mc).

The best output index for every analysis is selected among all these based on the minimum sum of the Paasche-Laspeyres spreads.

The sum of Paasche-Laspeyres spreads for each level of analysis and for each share value is included in the Figure D.1, D.2 and D.3. In every figure, the sum of the Paasche-Laspeyres spreads for all possible share of the regional production value is presented together with the sum of the Paasche-Laspeyres spreads for the output indexes considered using the products selection procedures without aggregation. The first set of statistics are represented by the dots, the second set is represented by the dashed lines. The red line is the statistics associated with the most reliable output index.

Regarding the output index at regional level, the most reliable index is the one that is constructed by considering as major products those that make for the 90% of the production values of all regions. The remaining 10% are aggregated into macro-categories.

For what regards the output indexes at the level of farms type and farms size, the most reliable indexes are obtained respectively by considering as major the products that make for the 60% of the production value at regional level and by not aggregating products into macro-categories but by

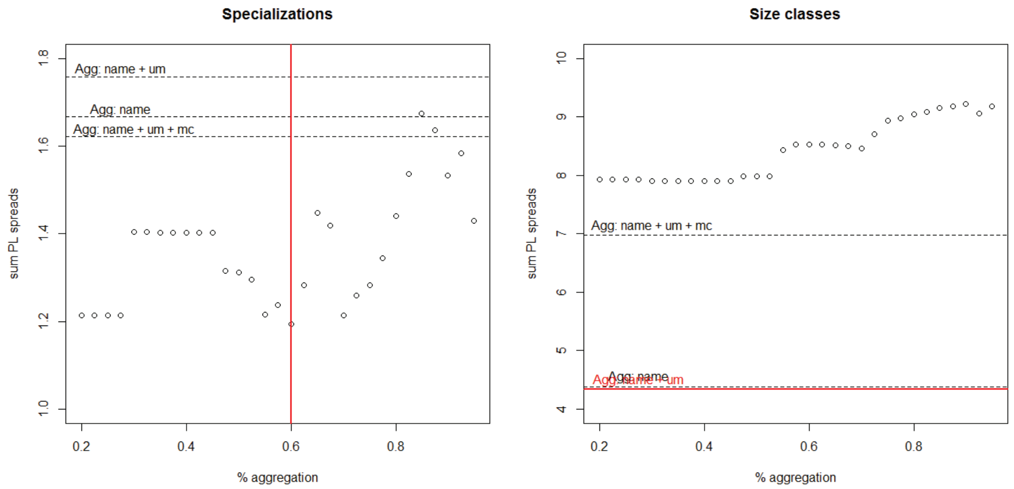

Figure D.2: PLS sums, types of farming and size classes

differentiating products based on their description together with their unit of measurement. The most reliable index at the level of NUTS3 is the one created by considering the products that make the first 20% of the production value in each year in year region as the *major* products as presented in Figure D.3.

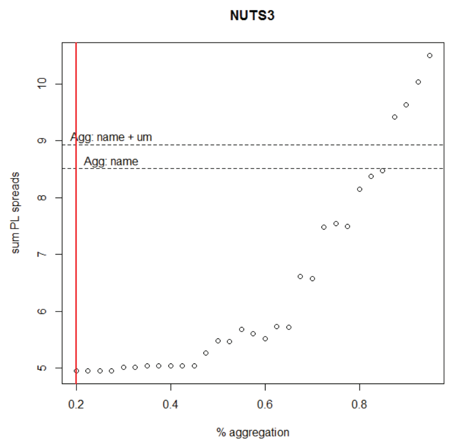

Figure D.3: PLS sums, NUTS3

Appendix E

Derivation of the input index

The inputs considered in the creation of an aggregate input index are the following: labor, fertilizers, pesticides, external services, water usage, electricity usage, seeds, feeding stuff, capital assets, land, reuses, and other general expenses such as commercialization, veterinary services, costs for the transformation of products and others.

In the creation of the aggregate input index, information regarding input prices and quantities are necessary. Such information can be often found within the FADN tables. However, the FADN database is not created for the generation of productivity statistics and in some instances some of the information required for the creation of aggregate indexes are missing.

The reason why they are not present might be different:

- because they are not collected. For example, salary of family workers is never registered;
- because information have been partially collected. For example water usage is collected on a voluntary basis only since 2011;
- because they might not exist. For example, price of capital does not exists because capital usage does not generally generate financial transactions;
- because they are not listed in the available database. For example, liters of motor fuel consumed on farm is registered on a voluntary basis and it is not present in the available database. However, CREA stores the information that might be available on request;
- because some data are collected only on a voluntary basis and cannot be used unless pre-processed.

When price and quantity data are not available, information has been imputed. However, the derivation of missing quantities and prices for these inputs could be a challenging task.

The imputation method can be done along the following lines:

– using partial information that is recorded in the survey (ex. average price of fertilizers per farm or region);
– using secondary external data (ex. interest rate was taken from the European Central Bank website);
– introducing assumptions (the shape of the decay function for asset efficiency is assumed);
– combining some of the previous ones (ex. to derive salary of family workers we take the net profit and split equally among the family members).

In what follows, the steps required for the derivation of the statistics necessary to create the aggregate input quantity index for each of the input are described. Also, a section with the spanning trees used in the creation of the aggregate input indexes is presented.

Labor

Quantities of labor supplied together with its corresponding price information can be found in the table LABOR COST. They are represented by hours worked and the corresponding average hourly salary plus average hourly social charges. This information is included in the table LABOR COST under the headings "HOURS", "SALARY", and "SOCIAL CHARGES". Data is divided by types of workers. There are four types of workers:
– seasonal workers;
– family workers;
– contract workers;
– full-time employees

Information regarding the salary received is not available for family workers. The salary for family workers needs to be imputed. Here, the salary of family workers is derived as a function of the financial performance of the farm. Net income for the accounting year is taken as the sum of the annual salary for all the family workers. In order to derive an average hourly salary, the sum is equally split by the number of family members and then divided by the number of hours worked.

Fertilizers

Quantities of fertilizers is obtained by deflating total costs for fertilizers found in the INCOME STATEMENT table by a corresponding average price. The average price if found in two possible ways. The first option is to deflate total costs for fertilizers by the total quantities used by using the detailed information available in the table FERTILIZERS. This option is used whenever the farm has disclosed, in any of the year of the panel, information regarding the price and quantities of the fertilizers it had used. Not always companies have disclosed such detailed information and therefore, this option is not always available. When farms decided not to disclose detailed information regarding their fertilizers usage, an average price is imputed on a regional basis. In practice, an average price for aggregate fertilizers is obtained in any of the year of the panel for all Italian regions. When farms did not disclose information regarding fertilizers price and quantities, this average price at regional level is used to deflate their total costs in order to obtain an approximate measure of quantity.

Pesticides

The procedure applied to derive the price and quantities of fertilizers is used to obtain the price and quantities for pesticides. Total costs for fertilizers at farm-level are obtained from the INCOME STATEMENT and deflated by an average price to obtain the corresponding quantity component. The average price is either obtained using the information available in the PESTICIDES table or by using an average price at regional level.

Energy

Two types of energy inputs are considered here: electricity and fuels for heating, and motor fuels. Only the value component of these two aggregates is available in the FADN database. Total costs for electricity and heating fuels are taken from two tables: table ANIMAL HUSBANDRY and table CROPS. In the two tables total cost for this energy components are divided by type of crops of by livestock. This information is aggregated at the level of farm in each of the accounting period.

Total costs for motor fuels are taken from the INCOME STATEMENT under the heading "Mechanization"[1].

The quantity component of energy use is not available in the database and is derived indirectly with the use of imported information from external data sources. In the present analysis, the price component of both energy types is taken from the EU agricultural price indexes. The price indexes used here are the price index for aggregate energy and for motor fuels. The quantity component is obtained by dividing the value component by its corresponding price component.

[1]The heading "Mechanization" is the English translation of the Italian word "Meccanizzazione".

Water usage

Price and quantity of water are obtained using the information available in the tables ANIMAL HUSBANDRY, CROPS and WATER USAGE. Total value of the water usage is taken from the tables ANIMAL HUSBANDRY and the table CROPS. In the two tables, total costs for water usage is available and split by type of crop or livestock product. The value component for water usage is obtained by summing up the costs for water usage for each agricultural product. The corresponding quantity component is computed in two ways:

1. if the company provided information regarding water volumes in the accounting year, than that water volume is the quantity component for that company in that year;

2. if the farm did not include any information regarding its water volume in the accounting year, than an average price is used to deflate the total value of water usage. The average price considered is given by the aggregate average price at regional level. This average price is obtained simply by dividing the total costs by the total amount of volume for the whole period 2008-2014 at regional level using information within the table WATER USAGE.

Services

The value and quantity components of external services received by farms is found in the tables LABOR, ANIMAL HUSBANDRY and CROPS.

Total costs for external services are obtained by summing the costs for external services for livestock and for crops. Hours worked are obtained by summing man- and machine-hour of external services available in the table LABOR.

In the presence of no working hours recorded for some farms and positive costs for external services, an average price for the accounting period at regional level is used to deflate the total value and to obtain the number of hours of external services demanded by farms. If that average price is not available for the current accounting period, an average price at regional level is used considering the full 2008-2014 period.

Seeds

Total costs for seeds are available in the FADN dataset. However, neither quantity nor price informations are given. Therefore, to retrieve the necessary price and quantity components, additional external information is used. The EU agricultural price index of seeds is used here as price component to deflate the value component and obtain the corresponding quantity component. EU price indexes are available only at national level and this means that the price component for seeds is equal across all farms considered in this analysis.

Feedingstuff

Feedingstuff is represented by straw and forage. The FADN database contains information on total costs for these inputs while, as for the case of seeds, no information regarding prices is available. Again, the price component for feedingstuff is taken from the EU agricultural price indexes. The same EU price index for feedingstuff is used here to deflate the total costs for feedingstuff for all farms.

Other costs

Other costs include costs for:

- costs for commercialization of products;
- veterinary expenses;
- costs associated with products transformation;
- other costs such as purchase of materials, phone bills, and other means of production.

As for seeds and feedingstuff information regarding this input is provided in the FADN database in the form of total costs. The price used here is the EU harmonized price index. The quantity component is thus obtained by deflating the value component by this price component.

Capital

Capital assets are one of the most important production factor in the agricultural production processes. The capital aggregate is composed of all durable equipment that are, typically, bought once and used as input in the production function of several accounting periods. In this analysis, capital assets are considered to be machines, buildings (excluding building dedicated to farmhouse services), livestock and plantations.

Despite its importance, assigning a quantity and price component to the amount of capital that enters the production function in each of the accounting period is a challenging task. The main challenge is that capital assets provide services to the production function without generating financial transaction.

Therefore, the quantity and price components of capital assets entering the production function need to be imputed under some assumptions. The following steps are made following the OECD (OECD, 2009) and Pierani and Rizzi (Pierani and Rizzi, 2009).

In particular, the main assumption used in measuring the quantity of capital input is that the amount of capital input entering the production function is proportional to the available productive stock of capital. The productive stock of capital is the amount of capital that is technically effective and can provide services to the production process. The productive stock is calculated by correcting past investment in capital assets by their loss in productive efficiency assuming a certain shape for the loss in efficiency. The function that relate the share of productive efficiency and the age of every asset is called *age-efficiency* function and is usually assumed to be either linear, geometric, hyperbolic, one-hoss shay-shaped, or of other shapes.

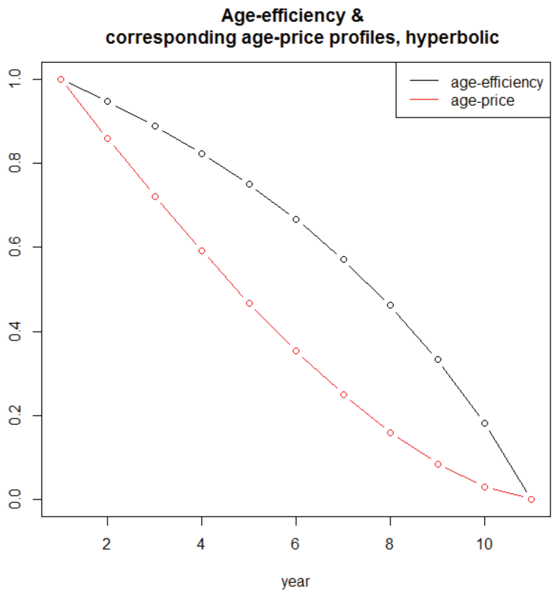

Figure E.1: Age-efficiency and corresponding age-price profiles, hyperbolic

Following, Ball et al. (Ball et al., 2010) and following Pierani and Rizzi (Pierani and Rizzi, 2009) the age-efficiency function used in this analysis is an hyperbolic age-efficiency function. The age-efficiency function is itself a function of a shape parameter, β, that determines the slope of the function.

For the different types of assets a different β is used. For machines and livestock β takes the value 0.5 while for buildings and plantations it takes the value 0.75.

There are many instances within the FADN database where the asset is recorded for a period of time that exceeds its expected life-length. In those instances, the approach taken here is to consider the productive efficiency of those assets at its minimum. Specifically, the level of productive efficiency that is attributed corresponds to the level of efficiency of the last year in which its productive efficiency was larger than zero.

With the capital stock obtained as the sum of efficiency-corrected series of past investments in each asset, it is possible to obtain the quantity component of capital services once their respective price component is determined in each of the accounting year.

The price component of each capital asset is called *user cost* or *rental price* because it represents the minimum a lessor would be willing to rent an asset for one accounting period. This minimum price represents all the costs associated with the use of the asset in the production processes of one year.

Typically, this price is composed of three components:

– the opportunity cost linked to the purchase of a durable asset;
– the depreciation of the asset, the value loss due to aging;
– revaluation, the expected price change of the asset in the specific accounting year.

In this analysis, the opportunity cost linked to the purchase of a durable good is taken to be the expected yield of the 10-year government bond for the period 2002-2013. This period was selected because it starts from the first years of the Euro Area, it is a relatively stable period, and because it is observable by farmers throughout the period 2008-2014.

Depreciation is the loss in the value of the asset due to aging. It is a function of the age of the asset and of its loss in productive efficiency. In particular, it can derived as the percentage change of value of the asset over time. The function that describes the price of an asset is called age-price function and it is closely linked to the age-efficiency function.

The last term is revaluation, the expected price change of the asset. In the present research, this term is obtained as the average price change of the nominal price index for each asset in the period 2008-2014.

The user cost formula is the following:

$$UC_t = Value_0 \theta_t (r^e + \delta_t(1+\tau^e) - \tau^e)$$

where $Value_0$ is the price paid for the capital asset, θ_t is discount factor for the price of the asset after t years of life, r^e is the expected interest rate, δ_t is the depreciation at year t, and τ^e is the expected value of the nominal price change.

With the price component and the capital stock component for each asset, it is possible to derive an aggregate quantity measure of capital services. This is obtained here by aggregating the capital stock of each vintage of capital asset in a multilateral Fisher index where the weights used for aggregation are represented by their corresponding rental prices.

The bilateral Fisher index number formula for the measurement of capital services considering two adjacent spatio-temporal unit, s and t, within the corresponding minimum spanning tree is the following:

$$CS_{s,t} = \sqrt{\frac{\bar{UC_s}' PS_t}{\bar{UC_s}' PS_s} \frac{\bar{UC_t}' PS_t}{\bar{UC_t}' PS_s}}$$

where $\bar{UC}$ is the vector containing the aggregate average user costs for the assets and PS is the vector containing the corresponding productive stocks.

The quantity index that is obtained by this multilateral aggregation represents the aggregate quantity component of capital services. The aggregate price component is obtained by deflating the sum of all rental prices by this quantity component.

Land

It is assumed that land does not depreciate. Its quality remains constant over time and therefore, land is treated separately from other capital assets. The information of quantity and price of the input land is found in the table LAND. Here, the quantity component of the input is the surface, in hectares, of land used in the agricultural production process while the price component is a fraction of the purchase price of the land. The fraction taken of the price of land is the rental price of land. The rental price of land is the percentage of the purchase price that is considered as opportunity cost. The rental price is just the purchase price times the average 10-year Italian bond yield over the period 2002-2013.

Reuses

The last input that is considered in the definition of the aggregate input index is represented by the products produced and reused on-site by farms. These products take the form of raw inputs in the production processes or as intermediate inputs in a more complex production process. The information on reuses is found in the table PRODUCTS. Reuses are available under the heading "Other uses". Their quantity and value are readily available in the table.

Minimum spanning trees of the input indexes

In this section the minimum spanning trees used in the construction of the chained input indexes at he level of FADN regions, types of farming, and size classes are presented.

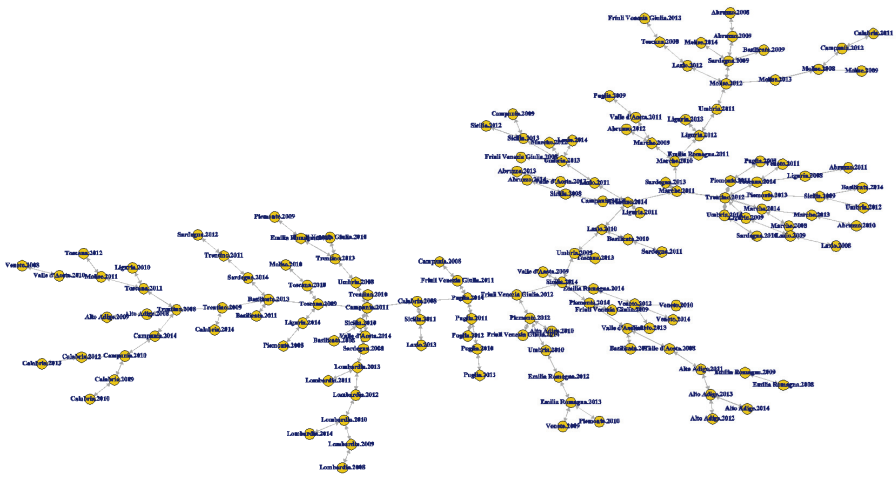

Figure E.2: MST input index, FADN regions

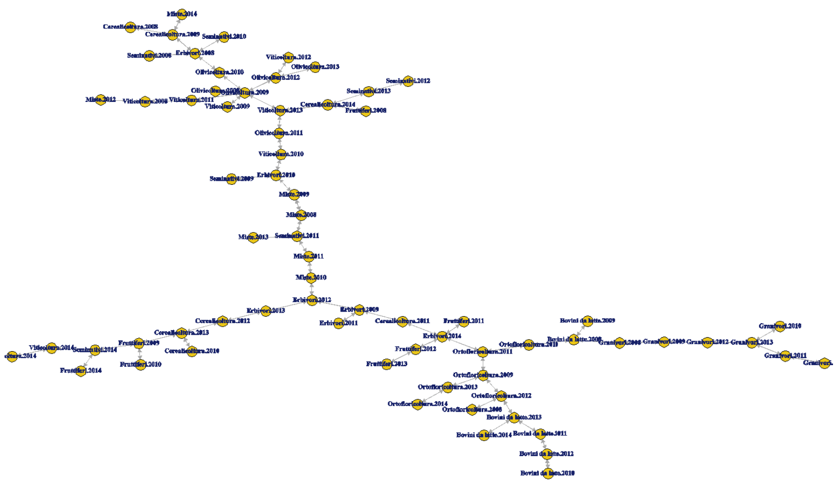

Figure E.3: MST input index, Types of farming

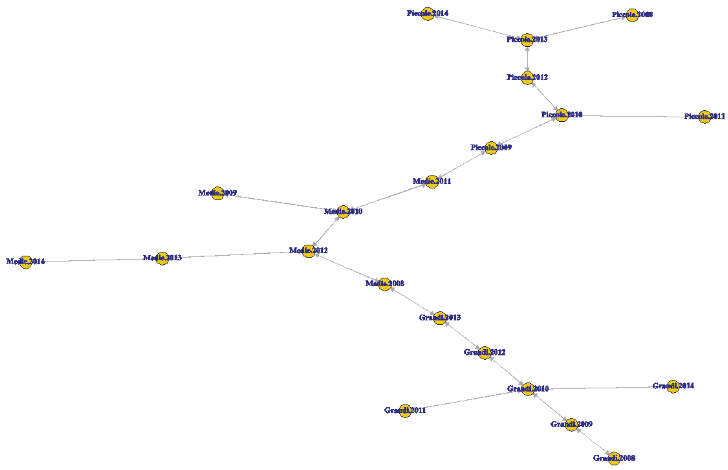

Figure E.4: MST input index, Size classes

Appendix F

Types of farming for the FADN

Code	TF	Code	TF	Code	TF	Code	TF
4110	Dairy	3610	Fruits	8232	Mixed	2220	Horticulture
4120	Dairy	3620	Fruits	6120	Mixed	2230	Horticulture
4310	Dairy	3630	Fruits	6130	Mixed	2310	Horticulture
4500	Dairy	3640	Fruits	7410	Mixed	2320	Horticulture
4700	Dairy	3650	Fruits	7420	Mixed	2330	Horticulture
1310	Cereals	3800	Fruits	8310	Mixed	6110	Horticulture
1320	Cereals	5011	Granivores	8320	Mixed	1410	Arable crops
1330	Cereals	5012	Granivores	8330	Mixed	1420	Arable crops
1510	Cereals	5013	Granivores	8340	Mixed	1441	Arable crops
1520	Cereals	5021	Granivores	8410	Mixed	1443	Arable crops
1530	Cereals	5022	Granivores	8420	Mixed	6040	Arable crops
4210	Grazing livestock	5023	Granivores	8430	Mixed	6050	Arable crops
4220	Grazing livestock	5031	Granivores	8440	Mixed	6062	Arable crops
4320	Grazing livestock	5032	Granivores	3300	Olives	1610	Arable crops
4410	Grazing livestock	7230	Granivores	3700	Olives	1620	Arable crops
4420	Grazing livestock	5110	Granivores	1430	Horticulture	1640	Arable crops
4430	Grazing livestock	5120	Granivores	2011	Horticulture	1650	Arable crops
4440	Grazing livestock	5130	Granivores	2012	Horticulture	1660	Arable crops
7110	Grazing livestock	5210	Granivores	2013	Horticulture	6140	Arable crops
7120	Grazing livestock	5220	Granivores	2021	Horticulture	6150	Arable crops
4600	Grazing livestock	5230	Granivores	2022	Horticulture	6160	Arable crops
4810	Grazing livestock	5300	Granivores	2023	Horticulture	3110	Wine
4820	Grazing livestock	6020	Mixed	2031	Horticulture	3120	Wine
4830	Grazing livestock	6030	Mixed	2032	Horticulture	3130	Wine
4840	Grazing livestock	7210	Mixed	2033	Horticulture	3141	Wine
7310	Grazing livestock	7220	Mixed	2034	Horticulture	3143	Wine
7320	Grazing livestock	8110	Mixed	6010	Horticulture	3510	Wine
3211	Fruits	8120	Mixed	6061	Horticulture	3520	Wine
3212	Fruits	8130	Mixed	1630	Horticulture	3530	Wine
3213	Fruits	8140	Mixed	2110	Horticulture	3540	Wine
3220	Fruits	8210	Mixed	2120	Horticulture		
3230	Fruits	8220	Mixed	2130	Horticulture		
3400	Fruits	8231	Mixed	2210	Horticulture		

Table F.1: Link between TF code and Types of farming as defined within the Italian FADN

Appendix G

Definition of size classes

According to the Italian FADN, under the classification "Dim_Economica_BDR", three classes are used for the definition of the economic size of farms: small, medium-sized and large. In the period 2008-2009 these classes are defined as a function of the Standard Gross Margins of farms. In the period 2010-2014 they are defined on the basis of the Standard Output.

Table G.1 presents the links between the SGM and SO classification with the classification provided in the Italian FADN.

The temporal distribution of the sampled farms using this classification is presented in Table G.2.

It is possible to notice that the number of sampled farms across the three classes changes remarkably in the two sub-periods in which the definition of economic size differs. The number of small farms in the period 2008-2009 stands at around 1,400 farms, the number of medium-sized farms stands at around 5,000 while the number of sampled large farms stands at around 4,500 farms. There seems to be a consistent reshuffling of sampled farms in the subsequent period as the annual number of small farms sampled increases at around 3,000, the number of medium-sized one decreases to around 4,400 farms and the number of sampled large farms decreases to around 3,600.

This reshuffling is due to two factors. From one side, it is due to the changing definition of economic size of farms. In 2008-2009 the concept of Standard Gross Margins were used to define the economic size of farms while in 2010-2014 the SGM was substituted with the concept of Standard Output. The second reason is due to the update, in 2010, of the standard coefficient for the measurement of the standard unit value for crop and livestock products. These two methodological changes resulted in the uneven distribution of sampled farms.

Such an uneven distribution could affect the comparability of the three size classes in the seven-year period considered. Thus, to make the three

Description	Period	Size class
1 - less than 2 ESU	2008-2009	Small
2 - between 2 and 4 ESU	2008-2009	Small
3 - between 4 and 8 ESU	2008-2009	Small
4 - between 8 and 16 ESU	2008-2009	Medium
5 - between 16 and 40 ESU	2008-2009	Medium
6 - between 40 and 100 ESU	2008-2009	Large
7 - larger than 100 ESU	2008-2009	Large
less than 4.000 euro	2010-2014	Small
between 4.000 and 8.000 euro	2010-2014	Small
between 8.000 and 25.000 euro	2010-2014	Small
between 25.000 and 50.000 euro	2010-2014	Medium
between 50.000 and 100.000 euro	2010-2014	Medium
between 100.000 and 500.000 euro	2010-2014	Large
between 500.000 and 1.000.000 euro	2010-2014	Large
larger than 1.000.000 euro	2010-2014	Large

Table G.1: Link between size classes within the Italian FADN database

Size class	2008	2009	2010	2011	2012	2013	2014
Large	4,657	4,500	3,662	3,604	3,725	3,728	3,402
Medium	5,295	5,181	4,352	4,488	4,356	4,548	4,512
Small	1,437	1,348	3,141	3,145	3,097	3,043	2,573

Table G.2: Sampled and represented farms, size classes

classes comparable throughout the whole period 2008-2014, the Italian FADN definition of size classes was changed. The changes regards both the concepts used in the definition of economic size and in the standard coefficient used in the measurement of the standard value of each crop and livestock product. First, the definition of economic size was only based on the concept of Standard Output. Secondly, the standard output for the period 2008-2014 was computed, when possible, using the unit standard coefficients used in the period 2010-2014. When the conversion was not possible, the standard unit coefficient remained unchanged. Afterwards, the aggregate Standard Output was recalculated at farm-level and farms were classified as small, medium or large based on the definitions used in the period 2010-2014.

The resulting temporal distribution of sampled farms across the three classes is presented in Table G.3.

Size class	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Large	3,628	3,537	3,662	3,604	3,725	3,728	3,402
Medium	4,613	4,525	4,352	4,488	4,356	4,548	4,512
Small	3,148	2,967	3,141	3,145	3,097	3,043	2,573

Table G.3: Sampled and represented farms, size classes revised

Appendix H

Time series of productivity

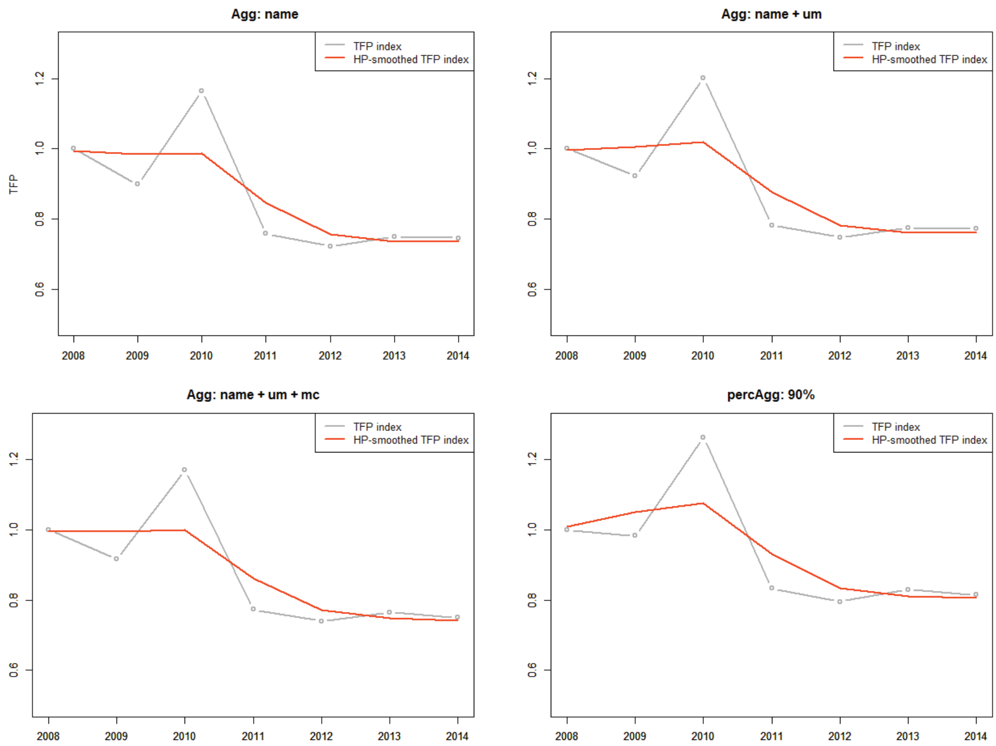

Figure H.1: TFP relative levels using different output aggregation methods, Italy

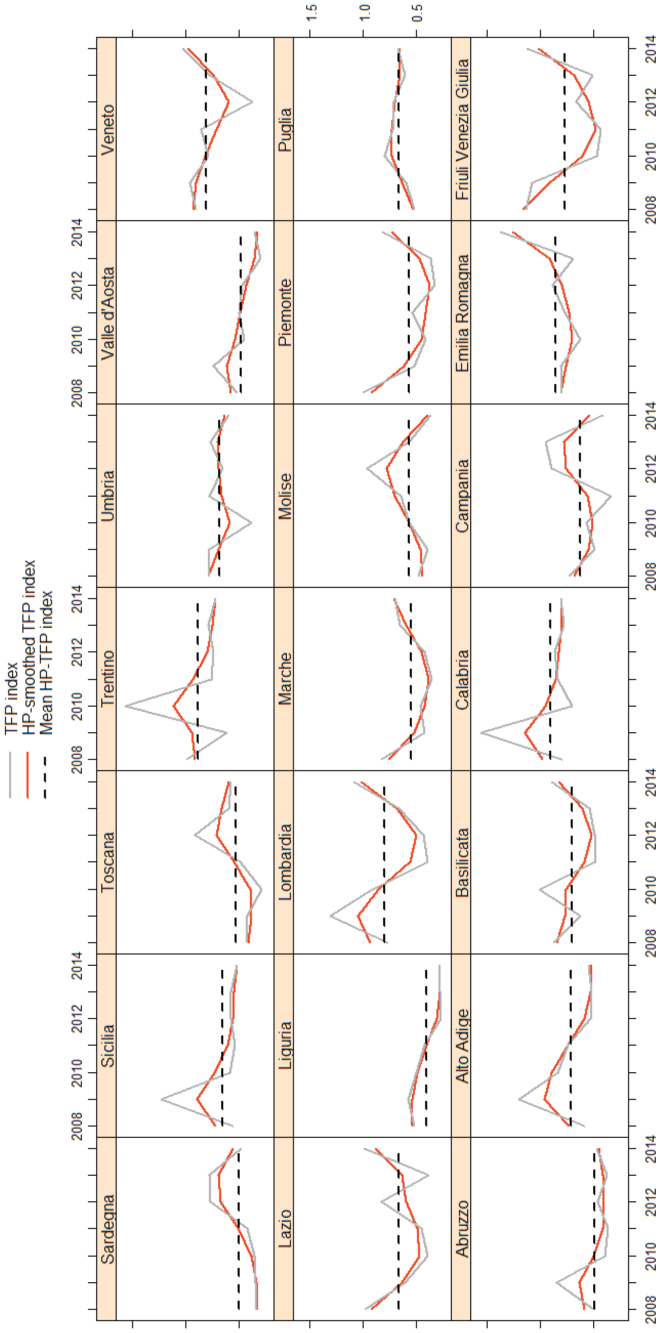

Figure H.2: TFP relative levels, FADN regions

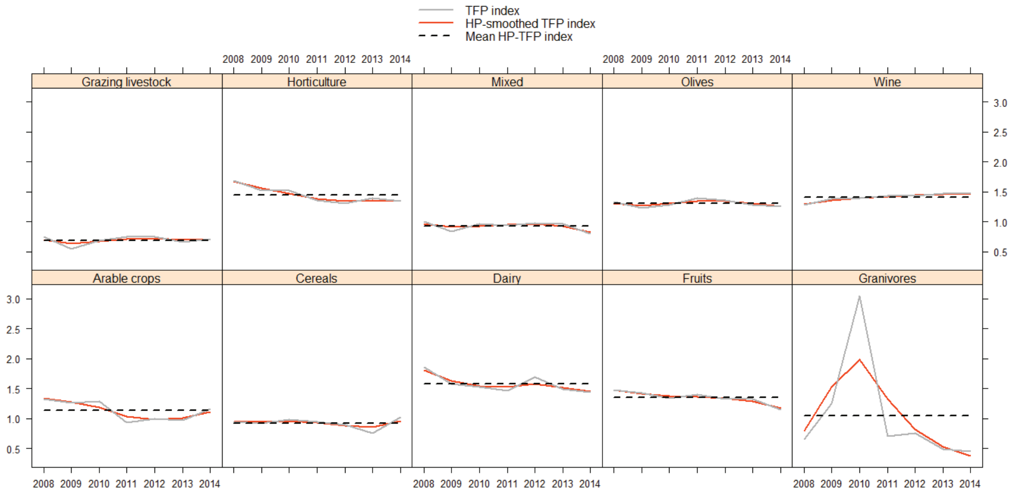

Figure H.3: TFP relative levels, types of farming

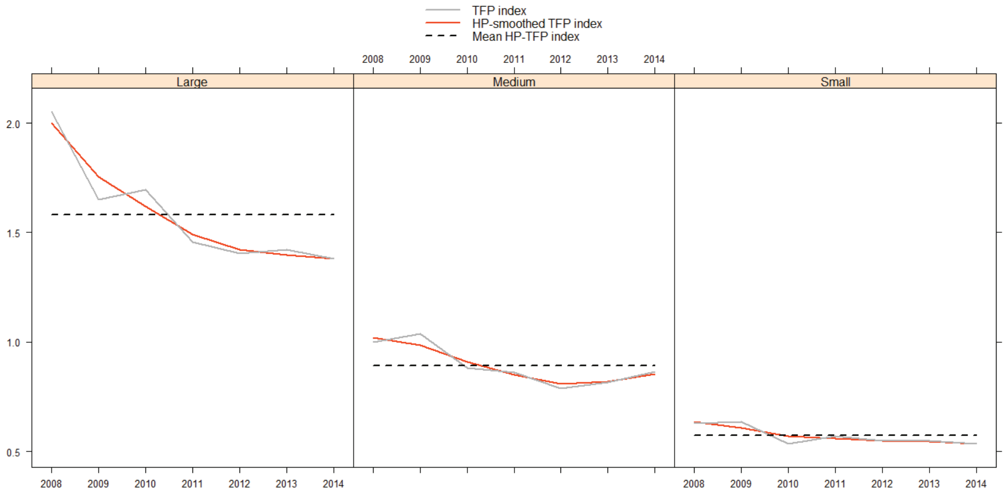

Figure H.4: TFP relative levels, size classes

Appendix I

BCLSDV estimator

This section takes after the derivation of the BCLSDV estimator presented the work of Elhorst (Elhorst, 2010).

In the BCLSDV estimator, the variables are first demeaned:

$$y^*_{it} = y_{it} - \frac{1}{T}\sum_{i=1}^{T} y_{it} \qquad\qquad X^*_{it} = X_{it} - \frac{1}{T}\sum_{i=1}^{T} X_{it}$$

Then the concentrated log-likelihood around δ is obtained using the residuals of the following two auxiliary regressions

$$y^*_t = \widetilde{X^*_t}^{'}\beta_0 + e_0$$

$$(I_T \otimes W)y^*_t = \widetilde{X^*_t}^{'}\beta_1 + e_1$$

where $\widetilde{X^*_t} = [y^*_{t-1}X^*_t]$. The resulting concentrated log-likelihood follows

$$logL_c = C - \frac{NT}{2}log[(e_0 - \delta e_1)^{'}(e_0 - \delta e_1)] + Tlog|I_N - \delta W|$$

This log-likelihood can be maximized with respect to δ. With the parameter $\hat{\delta}$ it is possible to derive all the remaining parameters of the model. In particular

$$\begin{bmatrix} \hat{\phi} \\ \hat{\beta} \end{bmatrix} = (\widetilde{X^*_t}^{'}\widetilde{X^*_t})^{-1}\widetilde{X^*_t}^{'}[y^*_t - \hat{\delta}(I_T \otimes W)y^*_t]$$

$$\hat{\sigma}^2 = \frac{1}{NT}(y^*_t - \hat{\delta}(I_T \otimes W)y^*_t - \widetilde{X^*_t}[\hat{\phi}\ \ \hat{\beta}^{'}]^{'})^{'}(y^*_t - \hat{\delta}(I_T \otimes W)y^*_t - \widetilde{X^*_t}[\hat{\phi}\ \ \hat{\beta}^{'}]^{'})$$

The LSDV estimator for a dynamic spatial model as used here is not consistent. Yu et al. (Yu et al., 2008) has derived the bias of the coefficients estimates of the dynamic spatial model

$$bias \begin{bmatrix} \hat{\phi} \\ \hat{\delta} \\ \hat{\beta} \\ \hat{\sigma}^2 \end{bmatrix} = \begin{bmatrix} \frac{1}{N} tr\{[(1-\hat{\phi})I_N - \hat{\delta}W]^{-1}\} \\ \frac{1}{n} tr\{W(I_N - \hat{\delta}W)[(1-\hat{\phi})I_N - \hat{\delta}W]^{-1}\} + \frac{1}{N} tr\{W(I_N - \hat{\delta}W)\} \\ 0 \\ \frac{1}{2\hat{\sigma}^2} \end{bmatrix}.$$

To correct the LSDV estimator the authors suggested the following correction

$$\begin{bmatrix} \hat{\phi} \\ \hat{\delta} \\ \hat{\beta} \\ \hat{\sigma}^2 \end{bmatrix}_{BCLSDV} = \begin{bmatrix} \hat{\phi} \\ \hat{\delta} \\ \hat{\beta} \\ \hat{\sigma}^2 \end{bmatrix}_{LSDV} - \left(\frac{-\Sigma}{NT}\right)^{-1} \frac{1}{T} bias \begin{bmatrix} \hat{\phi} \\ \hat{\delta} \\ \hat{\beta} \\ \hat{\sigma}^2 \end{bmatrix}.$$

where Σ is the asymptotic information matrix of the LSDV parameters estimates under the assumption of normality of ϵ. Following Elhorst (Elhorst, 2010) notation the information matrix is as follows

$$\begin{bmatrix} \frac{1}{\hat{\sigma}^2} {y^*_{t-1}}' y^*_{t-1} & & & \\ \frac{1}{\hat{\sigma}^2} {y^*_{t-1}}' \left(I_T \otimes \widetilde{W}\right) y^*_{t-1}\hat{\phi} & T * tr\left(\widetilde{W}\widetilde{W} + \widetilde{W}'\widetilde{W}\right) + \frac{1}{\hat{\sigma}^2}\left[\hat{\phi}\ \hat{\beta}'\right] \widetilde{X^*}' \left(I_T \otimes \widetilde{W}'\widetilde{W}\right) \widetilde{X^*} \left[\hat{\phi}\ \hat{\beta}'\right]' & & \\ \frac{1}{\hat{\sigma}^2} {X^*}' y^*_{t-1} & \frac{1}{\hat{\sigma}^2} {X^*}' \left(I_T \otimes \widetilde{W}\right) X^* \hat{\beta} & \frac{1}{\hat{\sigma}^2} {X^*}' X^* & \\ 0 & \frac{T}{\hat{\sigma}^2} tr\left(\widetilde{W}\right) & 0 & \frac{NT}{2\hat{\sigma}^4} \end{bmatrix}$$

where $\widetilde{W} = W(I_N - \hat{\delta}W)^{-1}$ and the upper diagonal elements of he matrix are not shown due to the symmetry of the matrix.

To be noted the difference between this matrix and the matrix presented in Elhorst (Elhorst, 2010). This is given in the cross-correlation term between the autoregressive parameter ϕ and the parameters associated with the exogenous explanatory variables β. While in Elhorst this term is given by $\frac{1}{\hat{\sigma}^2} {X^*_{-1}}' Y^*_{-1}$, here it is given by $\frac{1}{\hat{\sigma}^2} {X^*}' Y^*_{-1}$. This update in the formula was done because, after the differentiation of the likelihood function, we thought that the specific element of the var-cov matrix presented by Elhorst (Elhorst, 2010) was not correct.

Appendix J

Diffusion maps for Italian regions

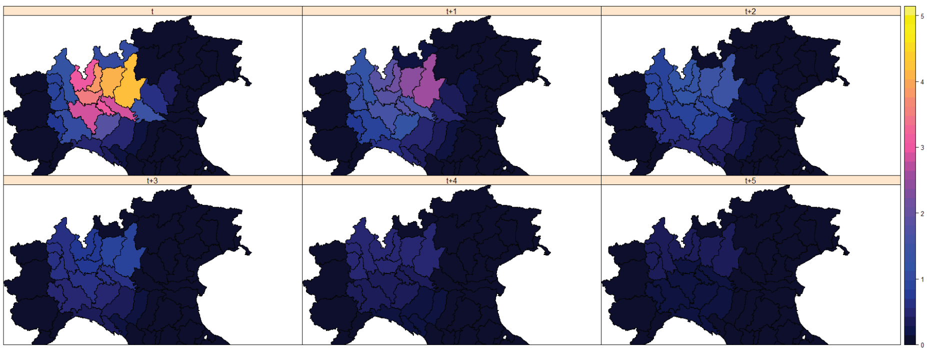

Figure J.1: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Lombardia

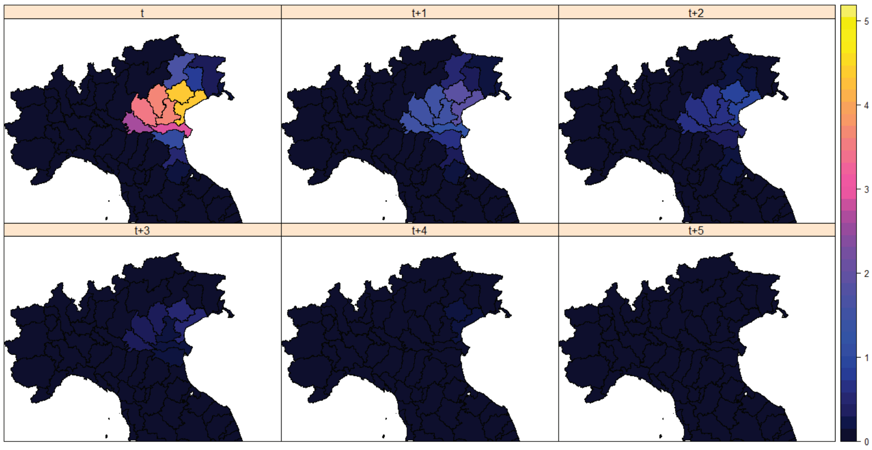

Figure J.2: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Veneto

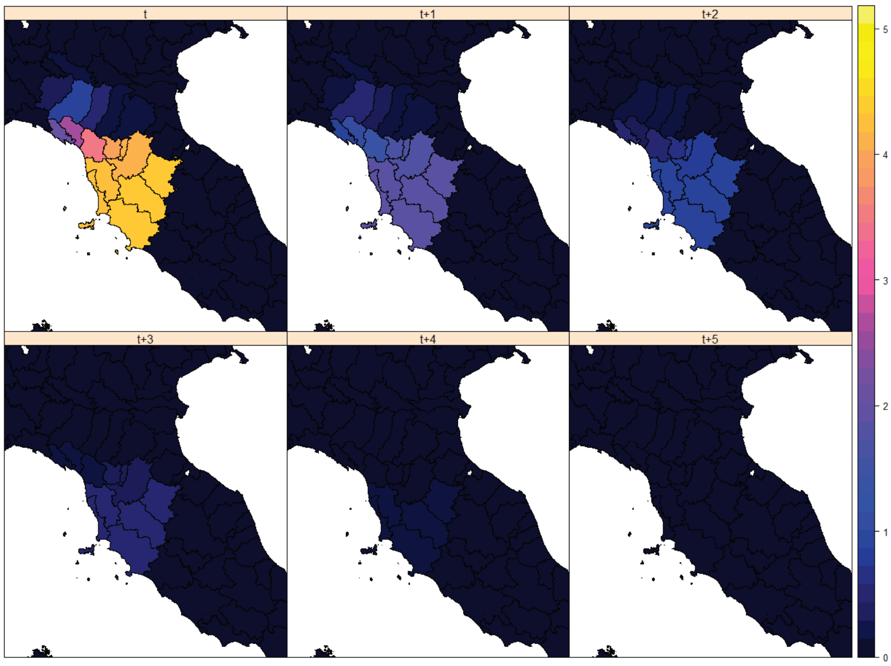

Figure J.3: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Toscana

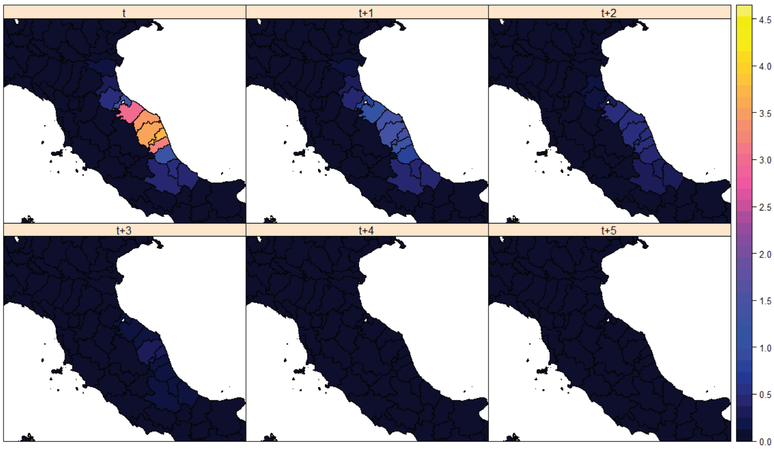

Figure J.4: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Marche

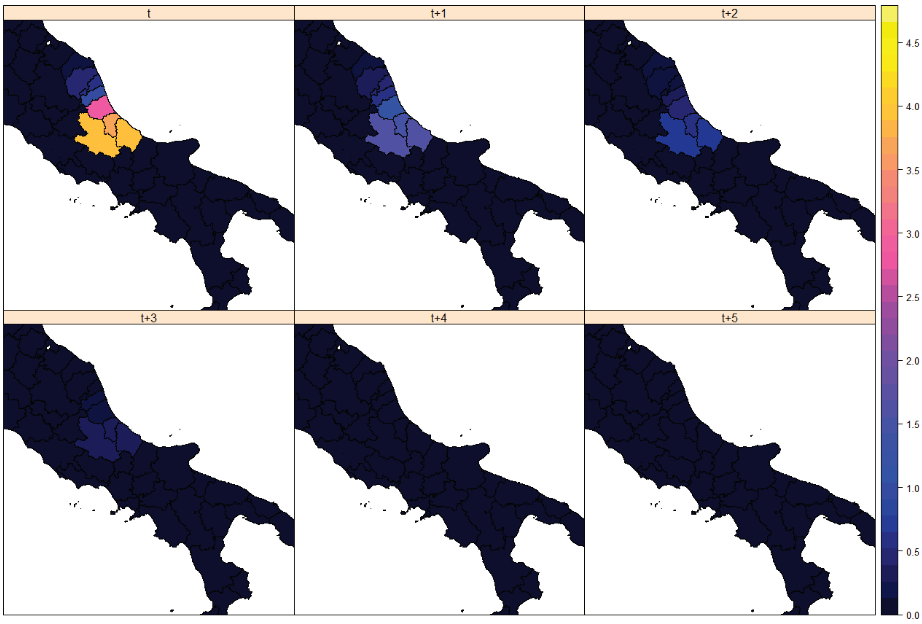

Figure J.5: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Abruzzo

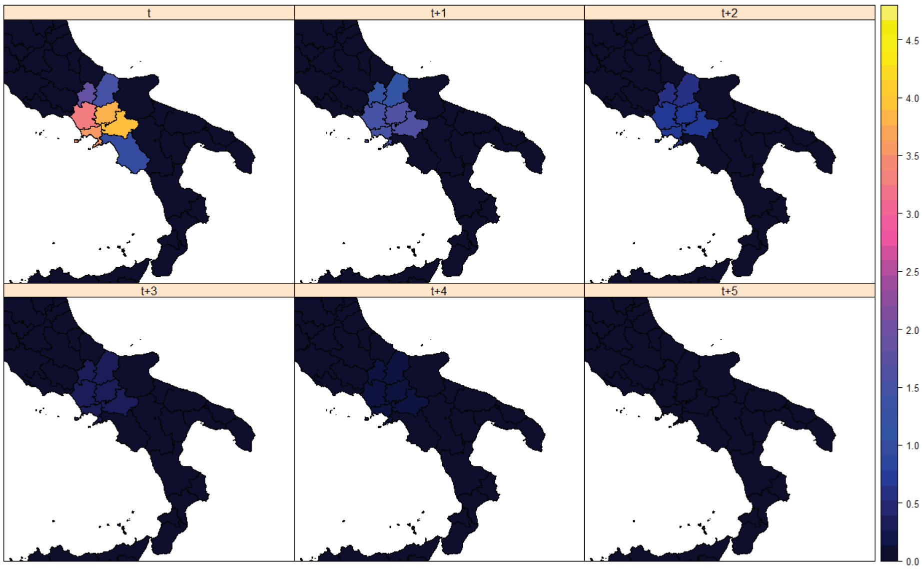

Figure J.6: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Campania

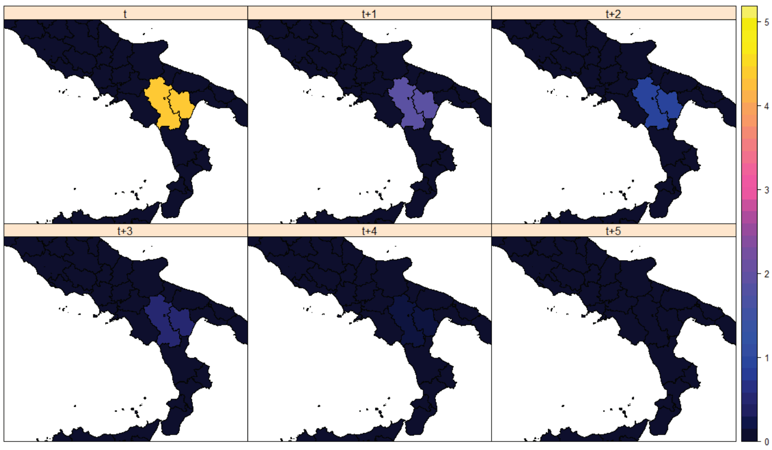

Figure J.7: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Basilicata

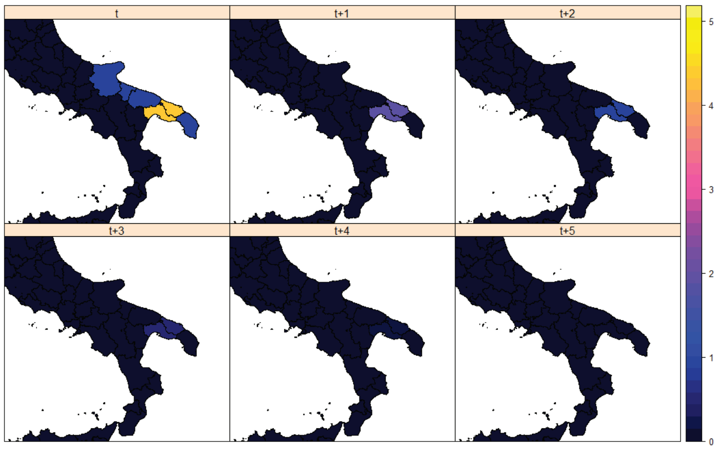

Figure J.8: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Puglia

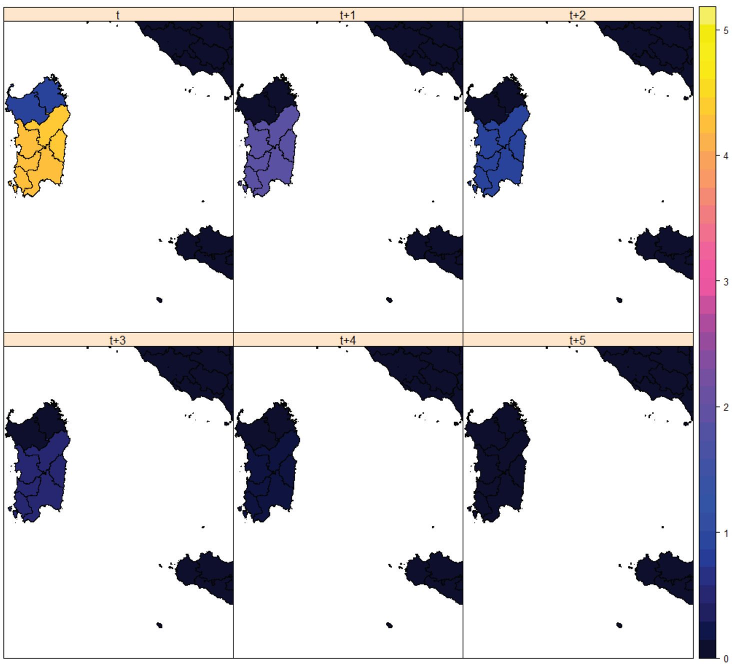

Figure J.9: Geographical space-time representation of the effects of a unitary productivity shock in the NUTS3 in Sardegna

Appendix K

Software

This research has been carried using the software R[1]. Data import, manipulation and analysis have been carried out using user-defined functions and functions written by other authors and included in packages downloaded from CRAN[2]. We would like to thank the whole R community for their support and provision of such functionalities.

The packages used in this analysis are: *sp*, *rgdal*, *spacetime*, *plyr*, *rgeos*, *maptools*, *spdep*, *lubridate*, *splm*, *reshape2*, *parallel*, *lattice*, *stargazer*, *maxLik*, *matrixcalc*, *mFilter*, *plm*, *raster*, *RColorBrewer*, *tseries*, *matrixStats*, *rts*, *msm*, *igraph*, *ape*.

The names of the authors of the packages used here are included in the Bibliography.

[1]https://www.r-project.org/

[2]Mirrors of the Comprehensive R Archive Network are available at https://cran.r-project.org/mirrors.html

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