Productivity and Convergence in European Agriculture

Abstract

In the paper we investigate relative productivity levels and decompose productivity change for European agriculture between 2004 and 2013. More specifically (1) we contribute to the debate whether agricultural Total Factor Productivity (TFP) has declined or not in the European Union (EU); (2) we compare the relative TFP level across EU member states and investigate the difference between 'old' member states (OMS, i.e. the EU-15) and 'new' member states (NMS) and (3) we test whether TFP is converging or not among member states. The empirical analysis applies the aggregate quantity framework developed in O'Donnell (2008), using country level panel data from the Economic Accounts for Agriculture for 23 EU member states. The results imply that TFP has slightly decreased in the EU over the analysed period; however there are significant differences in this respect between the OMS and NMS and across member states. Finally, our estimations support the productivity convergence hypothesis across the member states.

Keywords Total Factor Productivity (TFP) level, Agricultural productivity in the EU; Färe-Primont TFP index; TFP components; technical efficiency, scale efficiency, mix efficiency

JEL code Q12

1. Introduction

To ensure a fair standard of living for the agricultural community of the European Union (EU), improving productivity was a founding principle of the Common Agricultural Policy (CAP) enunciated in the Treaty of Rome. During recent decades agriculture has experienced major gains in productivity; however, the rate of increase has slowed down in developed countries in recent years (EC, 2012). European agriculture therefore faces a major challenge if it is to improve economic performance and living standards through productivity growth in rural areas. The intention of the Commission is clear: it desires to reverse – by 2020 – the recent trend of diminishing productivity gains. Identifying the main driver of productivity growth and the differences in productivity levels across countries is essential for achieving this aim. However, the literature is lacking in analysis and decompositions of cross country TFP (especially the level of TFP) in European countries.

Another key issue in modelling cross-country agricultural TFP differences is whether there is a tendency for productivity levels to converge to a common level, or whether differences in levels can continue indefinitely - or even increase over time (Timmer et al., 2010). As CAP is designed to ensure a fair standard of living for the agricultural community through productivity growth, it is important to understand whether countries with lower TFP levels are catching-up, as differences in TFP play the role in explaining income differences across countries (Hall-Jones, 1999). However, the number of pre-existing studies that have examined convergence across EU countries, especially following the Eastern enlargement of the EU, is limited.

Many studies have compared the development of agricultural productivity and efficiency in the EU over the past few decades (e.g. Ball et al., 2001, 2010; Brümmer *et al.*, 2002; Davidova *et al.*, 2003; Fogarasi and Latruffe, 2009; Swinnen and Wranken, 2010; Timmer et al., 2010, Cechura et al., 2014, Jansik et al., 2014; Jansik-Irz, 2014). However, most of the findings reported in these studies can be used only for bilateral comparisons (i.e. comparing two points in time). That is, there is a clear lack of TFP level estimations in the literature, only Ball et al. (2001, 2010), Timmer et al. (2010) and Cechura et al. (2014) provide information on relative TFP level across countries.

Moreover, earlier studies examined TFP levels across European countries, focusing only on 'old' member states (OMS, i.e. the EU-15) of the EU and the period up to 2007, (except Cechura et al., 2014.). Consequently, there is a clear lack of investigation into the comparison of agricultural TFP levels between the OMS and 'new' member states (NMS), and there is limited information about both the agricultural TFP growth and levels in the EU after 2007. Furthermore, ten countries joined the EU ten years ago, raising some obvious questions. How did these countries' TFP levels develop following EU accession? Have their TFP levels converged to those of the OMS? Are the drivers of productivity in the OMS and NMS similar or different?

The calculation of TFP change encounters many difficulties in terms of conceptual and methodological issues and data availability (Matthews, 2014). For example, DG Agri aims to measure the TFP using the Fischer index (EC, 2013). The Fisher index fails to satisfy the transitivity and identity axiom of index number theory. These failures mean that this index is not adequate to make multi-lateral comparisons and it is possible that these estimates indicate inter-temporal and/or inter spatial changes in productivity even when levels of inputs and outputs are exactly the same (O'Donnell, 2011a).

We contribute to the existing literature in at least two ways. Firstly, we use the Färe-Primont TFP index, which satisfies all economically relevant tests and axioms from index number theory (O'Donnell, 2012), providing new insights into the development of TFP in European agriculture. Our estimations can be compared with other TFP measures calculated using different methods and can serve as a basis for further discussion concerning methodological and empirical issues of TFP estimation in EU agriculture.

Secondly, within the still scarce literature on productivity convergence focusing on European countries (see e.g. Sonderman, 2012), there is, to the best of our knowledge, there is only a few studies that deals with the convergence of TFP across member states in the agricultural sector (see e.g. Sonderman, 2012; Cechura et al., 2014). In order to test for convergence, researchers usually apply either a cross-sectional or a time-series framework (more specifically, a unit root test framework). However, recently both the cross-sectional approaches (Quah, 1997; Evans, 1998) and the earlier (first generation) panel unit root tests (Breitung and Pesaran, 2007) have been criticised. Therefore, the additional contribution of this paper is that, in addition to the cross sectional tests, it applies recently-developed advances in panel unit root tests, namely a second generation panel unit root test.

In sum, the goal of the paper is to estimate relative productivity levels and decompose productivity changes for European agriculture from 2004 (from the first phase of eastern EU enlargement) to 2013. More specifically, our aims are: (1) to contribute to the debate whether agricultural TFP has declined or not in the EU; (2) to examine the differences between OMS and NMS; (3) to compare the relative TFP levels across EU member states; (4) to identify the main drivers of productivity growth and (5) to test whether TFP is converging or not among member states.

The remainder of the paper is organised as follows. We begin by briefly examining previous studies concerning cross-country productivity and convergence and then we outline the methods used in the analysis. Next, we present our dataset and then present our empirical results and the discussion of the results. Finally, we conclude.

2. Previous studies of cross country TFP patterns and convergence in Europe

In a recent, wide-ranging global assessment of agricultural production and productivity trends, Alston, Babcock and Pardey (2010) concluded that "agricultural productivity growth has slowed, especially in the world's richest countries". However, apart from the UK, they did not specifically investigate the situation in Europe (Alston et al., 2010; Wang et al., 2012). As highlighted by Matthew (2014), despite its policy importance, very little is known about TFP developments in European agriculture. The aim of this section is to summarize the findings of some pre-existing studies that have examined TFP development and convergence in EU agriculture.

In the early 2000s, Eurostat initiated an effort to develop a Multi-Factor Productivity (MFP) index for agriculture based on the Economic Accounts for Agriculture (EAA). The Eurostat index was published for a couple of years in the early 2000s, but was then discontinued (Matthew, 2014). Detailed information can be found about the results of this effort in a paper published by the European Commission in 2002. The authors highlight that the aim was not to compare growth rates, but rather to provide an overview of developments on the basis of Member States. The paper provides estimates for Multi Factor Productivity development in 10 EU countries and identifies increases in the MFP index of every country during the period of analysis.

Ball et al. (2001) examined relative levels of farm sector productivity for the United States and nine European countries for the period 1973 to 1993. They found that the difference in relative productivity levels narrowed significantly during this time. Their regression analysis-based findings identified the existence of a highly significant inverse relationship between the rate of productivity convergence and the initial level of productivity that is consistent with the 'catch-up' hypothesis. These results generally support the proposition that a positive interaction between capital accumulation and productivity growth exists, suggesting embodiment. In 2010, the authors revised and extended their estimates for 1973-2002 (Ball et al., 2010). Findings suggest that the level of relative productivity was the most important factor in determining international competitiveness. Sweden and Spain were the only European countries to achieve faster productivity growth in agriculture than the United States. Most remarkable was the rapid productivity growth of Spain. The authors provide several explanations for this. The first is what Gerschenkron (1952) termed "the advantages of relative backwardness"; countries that lagged particularly far behind the technological leaders had the most to gain from the diffusion of technical information and grew most rapidly. The second is capital deepening. Finally, Caselli and Tenreyro (2005) emphasize the importance of resource reallocation (particularly labour) between sectors as a contributor to rapid productivity growth.

Using the same dataset Wang et al. (2012) attempted to identify whether agricultural productivity growth is slowing in Western Europe. These authors applied statistical tests to the individual country TFP series to investigate whether any of them had experienced a significant slowdown in TFP growth, but their analysis did not reveal a significant slowdown in either TFP or labour productivity growth rates. The number of countries that have had lower TFP growth since 1983 is similar to the number of countries that have had higher. (Fuglie et al., 2012).

Swinnen et al. 2010 analysed the path of agricultural productivity in Central and Eastern European countries and the former Soviet Union. The authors organized the countries under analysis into six regional groups, including Central Europe (the Czech Republic, Hungary, Poland and Slovakia); the Baltic States (Estonia, Lithuania and Latvia), and the Balkans (Albania, Bulgaria, Slovenia and Romania). In Central Europe TFP increased slightly following the first years of transition – 0.4% annual growth between 1989 and 1992 –, and more significantly afterwards – 2.2% annually between 1992 and 1995, and 4.4% annually between 1995 and 1998. Research indicates a slowdown in TFP growth in the period 1998–2001, probably as a result of the substantial investment which was made into agricultural machinery and capital inputs. TFP fluctuated much more for the Balkan countries. From 1989 to 1992, TFP decreased by 4.1% per year. Later, there was a strong recovery (TFP increased by 7.5% per year in the period 1992–1995), but it fell again in the late 1990s when bad macro-economic policies resulted in an annual decline in TFP of 1.3% from 1995 to 1998. After 1998, when a series of important reforms were implemented in the region, productivity strongly recovered: from 1998 to 2001 TFP grew on average by 2.3% per year (Fuglie et al, 2012; Alston et al., 2010).

Coelli-Rao, 2005 examined growth in agricultural productivity in 93 countries over the period 1980 to 2000 and identified annual growth in total factor productivity of 2.1%. Moreover, the authors estimate that in Europe agricultural TFP grew by 1.01% annually; the speculation is that technological change was the most important determinant of TFP.

Fuglie, 2010 estimated TFP indexes by country, region and for the world as a whole using FAO annual data on agricultural outputs and inputs from 1961 to 2007. His findings show that in developed countries resources were being withdrawn from agriculture in increasing amounts during this period; TFP continued to rise, but the rate of growth in 2000-07 remained under 0.9% per year, the slowest of any decade since 1960s. According to his estimates, European agricultural TFP grew at 0,59% per year from 2000-2007.

Timmer et al., 2010 examined why European growth has slowed down since the 1990s while American productivity growth has speeded up. The authors provide a thorough and detailed analysis of the sources of growth from a comparative industry perspective. They argue that observing trends in MFP growth is crucial for understanding EU performance relative to the USA. In the EU, MFP growth rates declined in eighteen of twenty-six industries between 1980 and 1995, and from 1995 to 2005. The contribution of MFP growth also declined in most manufacturing industries, along with significant decelerations in agriculture, mining and construction. The paper demonstrates that in 2005 the EU led the USA in eight industries: mining, post and telecommunications, finance, and five manufacturing industries. However, major gaps relative to the USA existed in industries such as agriculture, business services, and, especially, electrical machinery. In most industries the productivity gap between the EU and the USA is significant: EU productivity levels are less than half those of the USA in agriculture, textiles, electrical equipment and utilities. The authors also looked at patterns of convergence across European countries from an industrial perspective over the period 1980-2005 but could not identify convergence in the agricultural sector.

Cechura et al., 2014 investigated catching up and falling behind processes in the milk sector for 24 EU Member States over the period 2004-2011. Their metafrontier estimates revealed that there are considerable differences in the productivity of milk production across the EU: Productivity is highest in the Old Member States, especially in the north west of the EU. The lowest level of productivity was found in Eastern Europe. The same structure for TFP development was found as for TFP. Moreover, these findings about technical change suggest that farm sizes are less than optimal in many regions of Central and Eastern Europe. The comparative analysis suggests that fewer farms could benefit from movement on the frontier in the NMS compared to the OMS. Moreover, there are no signs that poorly performing farms are catching up to better performing farms in these regions/countries.

Matthew, 2014 compared preliminary results from DG AGRI's computations[1] with data from the USDA database on international agricultural productivity growth which also contains TFP for EU countries.

The preliminary findings from DG AGRI's computations show that from 1995 until about 2002 TFP growth in the EU-15 was around 1.6% per annum. However, since then, EU-15 TFP growth in agriculture has stagnated, increasing by only around 0.3% per annum over the period 2002 to 2011. The only bright spot was TFP growth in the new Member States, which averaged around 1.6% growth per annum over the period 2002 to 2011. However, these countries account for a relatively minor share of total agricultural output in the EU, so TFP growth in the EU-27 over the past decade was a disappointing 0.6% per annum. Examining TFP growth by individual countries highlights the impressive productivity performance of some of the new members of the EU: the five countries in which TFP grew most significantly in the period 2001 to 2010 are all new Member States. Finland, Austria, Luxembourg and Denmark performed best in terms of TFP from the old EU-15 Member States, while the TFP of Spain, Ireland and Italy declined over this period. The DG AGRI figures build on the Eurostat EAA accounts (Matthew, 2014).

Agricultural TFP growth rates for the EU-23, according to the USDA estimates, were 2.1% for the decade 1991-2000, 2.2% for the period 2001-5, and 3.1% for the period 2006-2010. The new Member States show a different pattern. The corresponding figures for the EU-8 were 1.0% for the decade 1991-2000, 1.2% for the period 2001-5, and a disappointing 0.5% for the period 2006-2010. Thus, according to the USDA figures, productivity growth in the new Member States has been consistently lower than in the old Member States, and the gap has grown significantly in the most recent period (Matthew, 2014). The USDA figures build on FAOSTAT data for outputs and inputs.

3. Methodology

In this section we firstly present the measures of productivity and efficiency within the aggregate quantity framework developed by O'Donnell (2008). Secondly, we outline the Data Envelopment analysis (DEA) models applied to estimate these measures. Thirdly, the approach of cluster analysis is used to identify different production environments among European countries. Fourthly, the method to analyse convergence is summarised.

[1] Taken from a presentation by Tassos Haniotis at an IATRC symposium on agricultural productivity.

3.1. Measures of productivity and efficiency within the aggregate quantity framework

The productivity of a single-output single-input firm is usually defined as the output-input ratio. O'Donnell (2008) generalises this idea to a multi-output, multi-input case by formally defining the TFP of a firm to be the ratio of an aggregate output to an aggregate input.

Let $\boldsymbol{x}_{it} = (x_{1it,\dots,}x_{kit})'$ and $\boldsymbol{q}_{it} = (q_{1it,\dots,}q_{Jit})'$ denote the input and output vectors of firm *i* in period *t*. Then the TFP of the firm is:

$$TFP_{it} \equiv \frac{Q_{it}}{X_{it}} \text{ (1), where}$$

$Q_{it}\equiv$ Q($\boldsymbol{q}_{it}$) is an aggregate output and $X_{it}\equiv$ X($\boldsymbol{x}_{it}$) is an aggregate input (O'Donnell, 2011b). The associated index number that measures the TFP of firm i in period t relative to the TFP of firm h in period s is (O'Donnell, 2011a):

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it}/X_{it}}{Q_{hs}/X_{hs}} = \frac{Q_{hs,it}}{X_{hs,it}} \text{ (2), where}$$

$Q_{hs,it} = Q_{it}/Q_{hs}$ is an output quantitiy index; $X_{hs,it} = X_{it}/X_{hs}$ is an input quantity index.

O'Donnell (2008) uses the term *multiplicatively complete* to refer to TFP indexes that can be written in terms of aggregate input and aggregate output quantities.

Moreover, O'Donnell (2008) showed that any multiplicatively-complete TFP index can be exhaustively decomposed into a measure of technical change and measures of efficiency change. A possible decomposition may be written as follows:

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{TFPE_{st}}{TFPE_{hs}}\right),$$

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} \text{ (3), where}$$

TFP_t^* is the maximum possible TFP using the technology available at time t. The term TFP_t^*/TFP_s^* measures the change in the maximum TFP possible using the production technologies available in periods s and t, which can be seen as a measure of technical change. $TFPE_{it}$ measures the overall productive efficiency of a firm, so that the second term in equation 3 is a measure of overall efficiency change. This term can be further decomposed into various measures of technical, scale and mix efficiency change. For example,

$$TFPE_{it} = \left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSME_{it}}{OSME_{hs}}\right) \text{ (4), where}$$

$OSME_{it}$ is a combined measure of scale and mix efficiency change.

3.2. Estimation of Färe-Primont aggregate quantities and the components of the Färe-Primont TFP index

In order to estimate the TFP index in (2), different aggregator functions can be used, and these give rise to different TFP indexes. The only requirements is that they must be non-negative, non-decreasing and linearly homogeneous (O'Donnell, 2008). The class of these functions and the resulting TFP indexes include: Laspeyres, Paasche, Fischer, Lowe, Malmquist, Hicks-Moorsteen and Färe-Primont (O'Donnell, 2012).

Some of these functions can be calculated using observed input and output prices (e.g. Laspeyres, Paasche, Fischer and Lowe), while others can be calculated without price data (e.g. Malmquist, Hicks-Moorsteen and Färe-Primont). We did not have available price data to investigate our empirical questions, hence we had to choose an index number formula which can be estimated without price data.

Additionally, index formulas are often selected according to whether or not they satisfy certain axioms and tests. Laspeyres, Paasche, Fischer, Malmquist and Hicks-Moorsteen indexes all fail the transitivity test and generally can only be used to make single binary comparisons (O'Donnell, 2011b). As our aim is to compare TFP both among countries and over time, these indexes are not adequate to investigate our empirical questions. Therefore, in this paper we use the Färe-Primont index, which satisfies all economically-relevant axioms and tests from index number theory, thus it can be used to make both multi-lateral and multi-temporal comparisons.

The output- and input aggregator functions that underpin the Färe-Primont index can be written as follows (O'Donnell, 2011b):

$$Q(q) = D_o(x_0, q, t_0) \; (5)$$

$$X(x) = D_i(x, q_0, t_0) \; (6)$$

Estimating the Färe-Primont aggregate quantities involves estimating distance functions. Estimates of (5) and (6) can be obtained by first solving the following linear programs (LP) (O'Donnell, 2011b):

$$D_o(x_0, q_0, t_0)^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x_0'\beta : \gamma\iota + X'\beta \geq Q'\alpha; q'\alpha = 1; \alpha \geq 0; , \beta \geq 0\} \; and \; (7)$$

$$D_I(x_0, q_0, t_0)^{-1} = \max_{\phi,\delta,\eta}\{x_0'\phi - \delta : Q'\phi \leq \delta\iota + X'\eta; x_0'\eta = 1; \phi \geq 0; \eta \geq 0\} \; (8),$$

Furthermore, the first order partial derivatives of output and input distance functions with respect to outputs and inputs can be interpreted as revenue- and cost-deflated output and input shadow prices (e.g. Färe and Grosskopf, 1990; Grosskopf *et al.*, 1995). The shadow prices obtained by evaluating the first-order partial derivatives at the parameter values that solve LPs (9) and (10) are as follows (O'Donnell, 2011b):

$$p_0^* \equiv \partial D_o(x_0, q_0, t_0)/\partial q_0 = \alpha_0/(\gamma_0 + x_0'\beta_0) \text{ (9)}$$

$$w_0^* \equiv \partial D_o(x_0, q_0, t_0)/\partial x_0 = \eta_0/(q_0'\phi_0 + \delta_0) \text{ (10)}$$

Using the shadow prices, aggregate outputs and inputs can be then computed as follows (O'Donnell, 2011b):

$$Q(q) = q'p_0^* \text{ (11)}$$

$$X(x) = x'w_0^* \text{ (12).}$$

Moreover, in many DEA applications it is often the case that one or more estimated shadow prices are equal to zero; meaning that in these cases variations in associated outputs and inputs will not be reflected in the Färe-Primont estimates of output, input or productivity change (O'Donnell, 2011b). Hence, when any elements of α_0 and η_0 of the Färe-Primont index are equal to zero, O'Donnell suggests replacing α_0 and η_0 with sample average shadow prices. In this paper we follow this procedure.

In addition, the components – introduced in section 2.1 – of the Färe-Primont TFP index can be estimated using various DEA LPs.

A measure of the output oriented *technical efficiency* of firm i in period t can be obtained by solving (O'Donnell, 2012):

$$OTE_{it} = D_o(x_{it}, q_{it}, t) = \min_{\lambda,\theta}\{\lambda^{-1}: \lambda q_{it} \leq Q\theta; X\theta \leq x_{it}; \theta_\iota' = 1; \lambda, \theta \geq 0\}. \text{ (13)}$$

The output oriented *scale efficiency* can be estimated as (O'Donnell, 2011b):

$$OSE_{it} = OTE_{it}^{VRS}/OTE_{it}^{CRS} \text{ (14), where}$$

OTE_{it}^{VRS} and OTE_{it}^{CRS} are solutions to LP (6) under variable returns to scale and constant returns to scale respectively. OTE_{it}^{CRS} can be estimated if the condition of $\theta_\iota' = 1$ is deleted from Lp(6).

Measures of the output *mix efficiency* component can be obtained by solving the following LP (O'Donnell, 2012):

$$OME_{it} = \min_{\theta,z}\{\boldsymbol{p}_0^{*\prime}\boldsymbol{q}_{it}/\boldsymbol{p}_0^{*\prime}\boldsymbol{z}: \boldsymbol{z} \leq \boldsymbol{Q\theta}; \boldsymbol{X\theta} \leq \boldsymbol{x}_{it}; \boldsymbol{\theta}_\iota' = 1; \boldsymbol{\theta}, \boldsymbol{z} \geq 0\}, \text{ (15) where } z = \lambda q_{it}$$

The maximum possible TFP using the technology available in period t can be estimated as (O'Donnell, 2012):

$$TFP_t^* = \min_{\theta,z,v}\{\boldsymbol{p}_0^{*\prime} z: \boldsymbol{z} \leq \boldsymbol{Q\theta}; \boldsymbol{X\theta} \leq v; \boldsymbol{w}_0^{*\prime}\boldsymbol{v} = \boldsymbol{1}; \boldsymbol{\theta}_{\iota}^{\prime} = 1; \boldsymbol{\theta}, \boldsymbol{z}, \boldsymbol{v} \geq 0\}. \quad (16)$$

The difference in the maximum TFP possible in two periods can be seen as a measure of technical change.

3.3 Identifying groups of countries with different technologies using cluster analysis

In practice it is common to break the dataset into sub-samples in such a way that all observations in each sub-sample are observations on firms that operate in the same production environment. Each sub-sample is then used to estimate a separate frontier (O'Donnell, 2011a).

Our aim is to estimate relative TFP levels for 23 EU member states, thus the assumption of a common production environment is certainly strong. Therefore in the empirical analysis we account for different production environments and we estimate different technologies for groups of countries.

In the literature there are several techniques to identify different technologies within a sample. They can be identified using statistical procedures such as cluster analysis or econometric techniques (random parameter or latent class models) (Alvarez and del Corral, 2010).

In this paper we employ cluster analysis. In this we follow (with some modification) the approach of Sommer and Hines (1991), which uses Ward's minimum variance method to identify different production patterns in US agriculture. They used three types of variables: enterprise variables, resource variables and farm-non-farm interaction variables. We do not have the same variables as Sommer and Hines (1991); instead we used variables associated with types of production and weather conditions. In our opinion, these variables might be a good proxy to account for different production environments. The variables were transformed into a standard normal distribution (called Z-scores) with zero mean and unit variance to give all variables equal weight in the cluster analysis. As a result of this procedure, we identified five groups of countries and different frontiers were estimated for these groups.

Additionally, following O'Donnell (2012), to account for temporal variations in environmental factors, the frontiers were estimated using DEA models that allow for a small amount of technical regress. This involves using a moving window of observations to estimate the technology in each group. The size of the window was governed by the number of countries in each group (identified by the cluster analysis) and reflects a desire to estimate each regional frontier using at least twice as many observations as there are input and output variables in the dataset. The size of the window used to estimate the technology in each group is shown in Annex 1.

3.4 Econometric tests of TFP convergence

In order to test for convergence, researchers usually apply either a cross-sectional or a time series framework (Sonderman, 2012). As Liu at al., 2011 point out: two primary concepts of cross-sectional convergence have been used to measure convergence of productivity across countries or regions. The first notion, σ-convergence, considers whether the dispersion of TFP among countries or regions diminishes over time. The second, β- convergence, considers whether a steady-state TFP level exists for each geographic unit, i.e. whether the correlation between a state's initial TFP level and its subsequent growth in TFP is negative (Liu et al., 2011). However, as Hernández and Ávila (2015) highlights: cross-section tests of β-convergence are problematic since they (1) tend to over-reject the null of no convergence when countries are characterised by different steady states (Bernard and Durlauf 1996); (2) may render evidence of conditional convergence even when cross-country income distributions remain unaltered over time (Quah 1993); and (3) require to have identical first-order autoregressive dynamic structures across countries as well as to control for all factors causing cross-country steady-state income differentials (Evans and Karras 1996). These shortcomings can be overcome by employing time series methods. Therefore, in this paper we use only one cross-sectional test, namely the σ-convergence and we test for ß-convergence using time series approach.

The logic behind the time series approach can be summarised as follows (Sonderman 2012). Convergence can be assumed if idiosyncratic country-specific shocks only have temporary effects on productivity in a country relative to another country (or a country group average). In this case, the relative productivity levels would follow a stationary process. Without stationarity, relative productivity shocks would lead to permanent deviations. This definition of convergence is often referred to as stochastic convergence following Carlino and Mills (1993) and Evans and Karras (1996). According to this definition, convergence can be tested in a unit root test framework.

Three main types of unit root tests can be distinguished: univariate root tests, and first- and second generation panel unit root tests. Univariate unit root tests are only adequate to investigate convergence between two countries (Sonderman, 2012) and they can lead to misleading results, especially in small- and moderate-sized samples (Liu *et al*, 2011). The extension of these tests to the panel framework has significantly influenced the literature. Over the previous decade, a number of panel unit root tests have been developed (e.g. Baltagi, 2008). However, recent advancements in panel-data econometrics indicate that first generation panel unit root tests, which do not account for cross-sectional dependence (CD), tend to over-reject the presence of unit roots (Baltagi *et al*., 2007; Eberhardt and Teal, 2013). This issue led to the development of second generation panel unit root tests, e.g. Bai and Ng (2004) and Pesaran (2007) panel unit root tests. These tests explicitly allow for CD in the data and therefore have better performance than first-generation panel unit root tests (Eberhardt and Teal, 2013).

In our empirical analysis of convergence the assumption of cross-sectional independence appears to be unreasonable according to the literature, because various studies using cross-country data indicate that time series are contemporaneously correlated (Breitung and Pesaran, 2007; Sonderman, 2012). In order to check it empirically in the database used, before carrying out a panel unit root test, firstly we investigated the potential for CD in the obtained TFP scores, applying the Pesaran (2004) CD test. As it revealed evidence of CD, we used a second generation panel unit root test. However, some of the second generation panel unit root tests require a panel dataset with large time dimension, e.g. the Bai and Ng (2004) test. As in our dataset the time dimension is relatively small, we used the Pesaran (2007) test, which performs accurately also with small samples (Moscone and Tosetti, 2009).

4. Data

For the empirical analysis we used country-level panel data from the Economic Accounts for Agriculture (EAA) database covering the period 2004-2013. For the land input, we used data from the FAOSTAT database. Data for the land input was only available until 2012, however in the land input there were no remarkable changes in recent years, therefore we estimated TFP for 2013 with land data from 2012. We estimate TFP levels in the EU-15 countries and in eight of the ten countries that joined the EU in 2004. Malta and Cyprus were excluded because of missing data.

For the purpose of DEA frontiers estimation, two outputs: q_1 crop output and q_2 animal output at constant prices (2005=100%); and four inputs (labour in annual work unit [x_1], utilised agricultural area in hectares [x_2], fixed capital consumption (FCC) at constant prices

(2005=100%) [x_3] and total intermediate consumption (TIC) at constant prices [x_4]) were used. The output variables were considered at producer prices.

For the identification of different technological and environmental characteristics with cluster analysis, we used two groups of variables: (1) the share of main agricultural products and secondary activities in total output and (2) variables accounting for environmental conditions: mean annual temperature and average precipitation. The variables used and the averages over 2004-2013 of the associated z-scores are shown in Annex 2.

5. Results

5.1. Groups of countries obtained by cluster analysis

By means of cluster analysis we obtained five groups of countries with different production environments. Group 1 contains: Austria, France, Ireland, Luxemburg and Slovenia. Group 2 includes: Belgium, Denmark, Germany, the Netherlands and the United Kingdom. Group 3 includes: Czech Republic, Hungary, Poland and Slovakia. Group 4 contains: Estonia, Finland, Latvia, Lithuania and Sweden. Group 5 includes: Greece, Italy, Portugal and Spain (Figure 1).

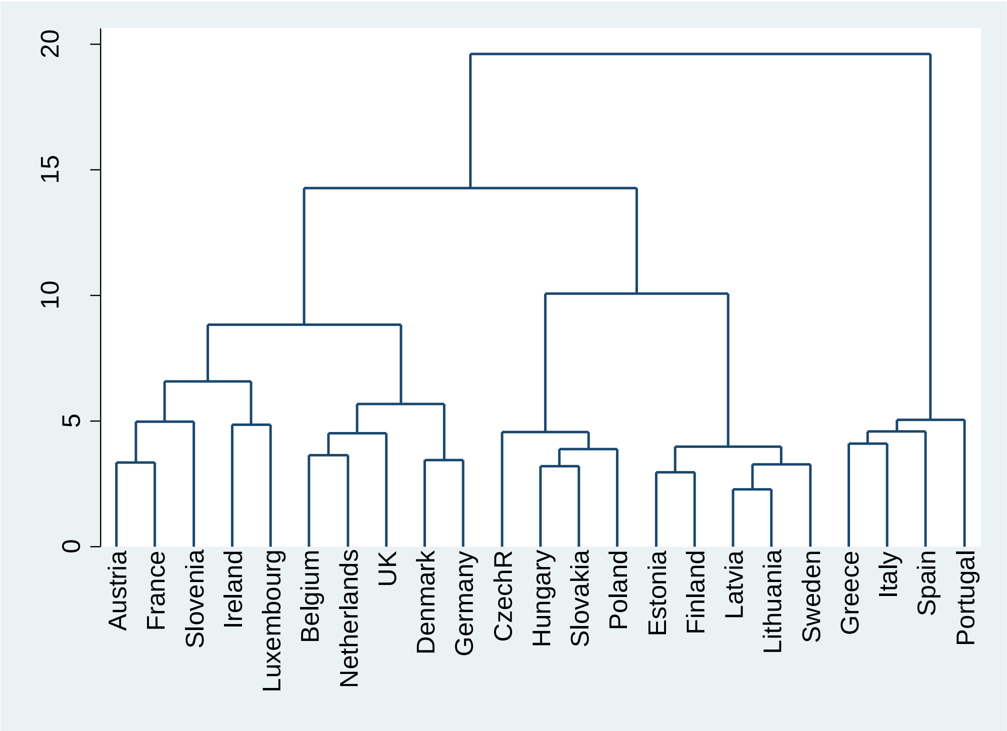

Figure 1: Groups of EU countries obtained by cluster analysis
Source: own composition

In the next step, different frontiers were estimated for these groups to estimate the TFP levels for individual countries. The results are presented in the following sections.

5.2.TFP development in the European Union

We focus on two issues in the TFP development of the EU. First, we are interesting for the trend in TFP during analysed period. To calculate the EU-level aggregate TFP we employ weighted arithmetic averages of the estimated TFP levels of the 23 EU member states using the country's share of total output as weights. Short-term fluctuations in weather events and macroeconomic movements (business cycles) may significantly affect on TFP estimate. These events might affect our estimates, even if we used the moving window method in the construction of TFP indexes. One approach to analyze fluctuations and trends applying the Hodrick-Prescott filter (H-P filter, Hodrick and Prescott (1997)) to smooth the variation in the TFP series. We smoothed the TFP series using the Hodrick-Prescott Filter setting λ=6.25 for annual data as recommended by Ravn and Uhling (2002) and Fuglie (2010). Our estimations suggest a declining trend in the TFP at the aggregated EU-level (Figure 2.A.). To check evolution of the TFP trend we regress TFP against time trend. The coefficient of time trend is negative but insignificant, that is we cannot confirm the decreasing trend in the TFP development.

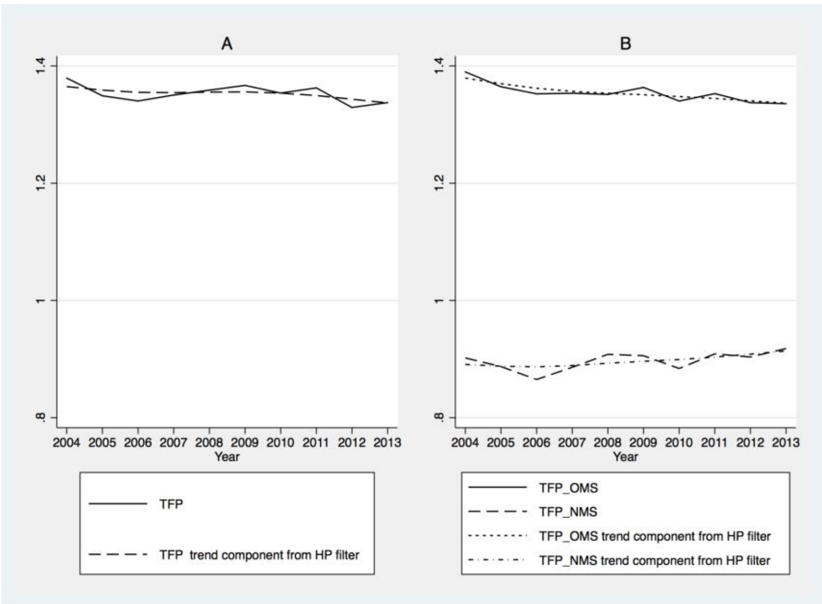

Figure 2A-2B: TFP development in the European Union

Source: own composition

Second, we concentrate on the possible differences in the TFP development between the OMS and the NMS. The estimated TFP index is transitive therefore both the development of TFP and the difference between the TFP level in the OMS and NMS can be directly compared. Our estimations indicate that the TFP level is much higher in the OMS comparing to the NMS, suggesting a higher technological level (Figure 2.B.). However, our calculations show a different trends in two country groups. While the TFP in the OMS reveal a declining trend, the NMS present a rather growing trend. Simple regressions against time trend confirm the significant growing trend for the NMS and significant declining trend for the OMS. The reasons can include similar elements as Ball et al. (2010) explain the rapid growth in Spain between 1973 and 2002. Namely, the advantages of relative backwardness; those countries that were particularly far behind the technology leaders had the most to gain from diffusion of technical information and proceeded to grow most rapidly. Furthermore, the rate of catchup should accelerate as these countries become more integrated with the rest of Europe. A second is capital deepening. Before and after accession NMS were able to access to higher amount of investment subsidies, which facilitated the capital deepening process. Third, one can argue that integration in the European Union has led to increased specialization in production of goods that are competitive in export markets.

5.3. Differences in TFP level among EU member states

Our second aim was to compare the TFP level its development among EU member states. In Figure 3, the black triangles represents estimates of TFP levels for member states in 2004, whereas the grey circles denotes estimates for 2013. The applied TFP index is transitive and can therefore be used to make meaningful comparisons of performance across both countries and time; i.e. both the rank of TFP level among countries and the dynamics of TFP change can be compared.

The productivity level was rather stable; the rankings between the countries did not change significantly between 2004 and 2013 (Figure 3). Both in 2004 and 2013 Belgium, the Netherlands and Denmark were the most productive countries. Although in Belgium there was a marked decrease in TFP level, it still remained one of the most productive countries. In contrast, it appears that the agricultural sector was the least productive in Latvia, Lithuania, Estonia and Slovakia.

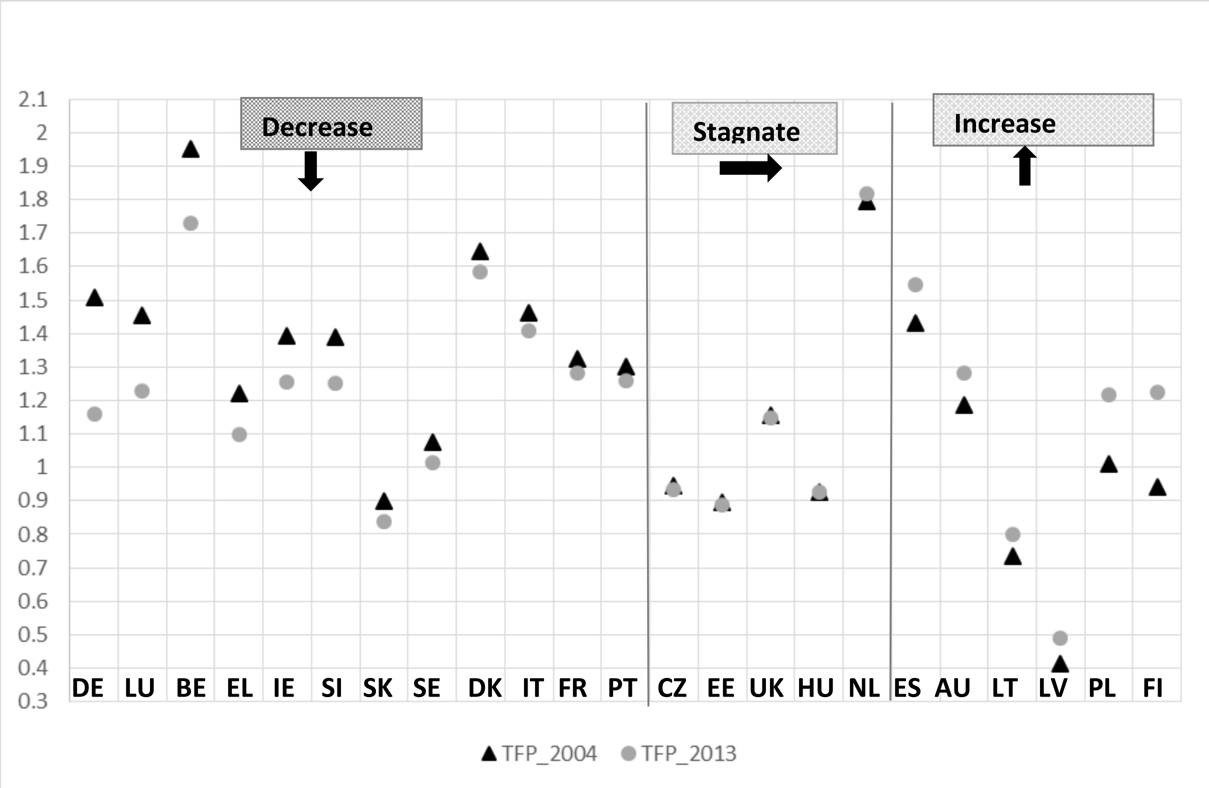

Figure 3: TFP Level in EU member states in 2004 and 2013
Source: own composition

In order to make it easier to follow the changes in TFP level, we divided the countries into three groups. Group 1 contains countries where TFP increased; Group 2 contains those where TFP stagnated and Group 3 contains countries where TFP decreased. The biggest increases occurred in Finland, Poland and Latvia and the biggest decreases were observed in Germany, Luxemburg and Belgium. The decomposition of TFP change could provide further information concerning the reasons for these changes. Therefore, in the next step of our analysis we investigate the annual rate of growth in TFP and the decomposition of TFP growth. The results are presented in the next section.

5.4. Annual rates of growth in TFP and efficiency

The annual growth rate of variables (V_k) reported can be calculated using: $\Delta \ln V_k \equiv \ln (V_{ta}/V_{ts})/(t_a-t_s)$, where t_a is an actual period, t_s is a starting period and k=TFP, TFP*, TFPE, OTE, OSME. The estimated growth rates are additive, which means that: (1) $\Delta \ln TFP = \Delta \ln TFP^* + \Delta OTE + \Delta \ln OSME$ (O'Donnell, 2010). Hence, it is possible to identify the main driver of TFP growth, which can be important for agricultural policy implication.

In Table 1 the values that are marked with an "h" are the highest among the 23 countries analysed, while those marked with a "l" are the lowest. The annual growth rate in TFP, at 2.89%, was the highest in Finland, due to a 1.32% increase in technological change and a 1.57% increase in overall efficiency measure. It was the lowest in Germany, where the estimated annual growth rate of TFP was -2.91%, the major driver of this TFP decrease being scale and mix efficiency. This means that in Germany the TFP decrease was mainly due to the changes in the scale and scope of production. Investigating the changes in output and input volumes in Germany, we see that there were huge changes both in the outputs and inputs of agricultural production; the aggregate output markedly decreased and at the same time the aggregate input increased. As a result of these changes the production deviated from the optimal point of the mix unrestricted frontier, i.e. from the point of maximum possible TFP. Consequently, these results imply that there is room to improve the TFP in Germany through the adjustment of the scale and scope of production. The technical efficiency component was rather stable in every country, considerable changes occurd only in Germany, Slovenia and in the UK; it decreased in Germany and Slovenia, whereas it increased in the UK. These findigs shows that Germany and Slovenia deviated from the available technological level, however the UK moved closer the available technological frontier over the analysed period.

Table 1. Annual growth rates in TFP and efficiency (%)

	TFP	**TFP***	**TFPE**	**OTE**	**OSME**
Austria	0.87	-0.56	1.43	0.00	1.43
Belgium	-1.34	-0.80	-0.54	0.00	-0.54
Czech Rep.	-0.13	2.05	-2.18	0.00	-2.18
Denmark	-0.43	-0.80	0.37	0.00	0.37
Estonia	-0.11	1.32	-1.43	0.00	-1.43
Finland	*2.89*^{h}	1.32	*1.57*^{h}	0.00	*1.57*^{h}
France	-0.37	-0.56	0.19	0.00	0.19
Germany	*-2.91*^{l}	*-0.80*^{l}	-2.11	-0.33	-1.78
Greece	-1.18	0.74	-1.92	0.00	-1.92
Hungary	-0.01	2.05	-2.06	0.00	-2.06
Ireland	-1.17	-0.56	-0.60	0.00	-0.60
Italy	-0.40	0.74	-1.14	0.00	-1.14
Latvia	1.84	1.32	0.52	-0.01	0.53
Lithuania	0.95	1.32	-0.37	0.00	-0.37
Luxembourg	-1.88	-0.56	-1.32	0.00	-1.32
Netherlands	0.13	-0.80	0.93	0.00	0.93
Poland	2.05	*2.05*^{h}	0.00	0.00	0.00

Portugal	-0.36	0.74	-1.11	0.00	-1.11
Slovakia	-0.76	2.05	-2.82[l]	0.00	*-2.82*[l]
Slovenia	-1.16	-0.56	-0.60	-0.17	-0.43
Spain	0.85	0.74	0.11	0.00	0.11
Sweden	-0.64	1.32	-1.97	0.00	-1.97
UK	-0.08	-0.80	0.72	*0.37*[h]	0.36
Old MS	-0.40	-0.56	1.43	0.00	-0.36
New MS	0.33	-0.80	-0.54	-0.02	-1.10
EU_all	-0.15	2.05	-2.18	-0.01	-0.62

Source: own composition

In the last row of Table 1 the averages of the OMS, NMS and the 23 analysed member states are reported. The TFP slightly decreased in the EU, however, there are considerable differences among the OMS and NMS as well as among countries.

5.5. Investigation of TFP convergence

In this section, we present the results of two convergence hypothesis tests. We start by testing for σ-convergence and then examine the existence of ß-convergence.

The most frequently used summary measures of Sigma-convergence are the standard deviation or the coefficient of variation of specific variable (e.g. GDP per capita, TFP.). However, several other indices exist (see Jenkins and Van Kerm, 2009). We use four measures: the coefficient of variation, the Gini coefficient, the Theil index and the Mean Logarithmic Deviation (Figure 4)

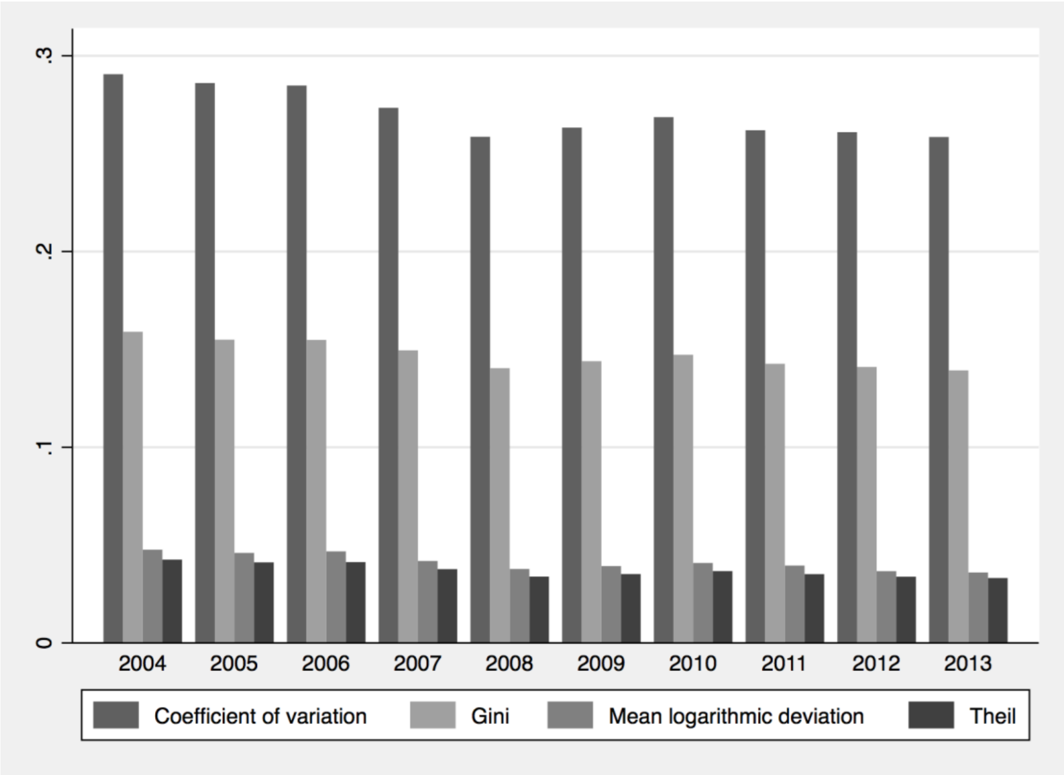

Figure 4: Measures of Sigma-convergence between 2004 and 2013
Source: own composition

Our estimations indicate that the dispersion presents a declining trend irrespective to different indicators (Figure 4).

In the next step of our examination we regress TFP against time trend to check formally the existence of σ-convergence. To test formally for σ -convergence, we use changes in the variance across countires to measure changes in TFP dispersion. Following Sala-i-Martin (1996) and Liu et al., (2011), the applied model is defined as follows:

$$var_t(\ln TFP) = \alpha_1 + \alpha_2 t + \epsilon_t, \text{ where}$$

$var_t(\ln TFP)$ is accross-countries variance of the logarithm of TFP in period t, α are parameters and ϵ is a zero-mean random disturbance term. A significantly negative coefficient associated with the time variable t, i.e. $\alpha_2 < 0$, implies σ – convergence.

The results for the σ -convergence test are presented in Table 2 and Table 3.

Table 2. Test for TFP σ-convergence

	Coefficient of variation	Gini	Theil	Mean logarithmic deviation
time	-0.004***	-0.002***	-0.001***	-0.001***
constant	0.290***	0.159***	0.043***	0.048***
R^2	0.7698	0.7900	0.7919	0.8088
n	10	10	10	10

Source: own composition

Table 3. Test for TFP σ-convergence

Variables	Coefficient	Standard Error	t	Prob |t|>T*	95 % Confidence Interval	
Intercept	.10923***	0.00325	33.56	0	0.10285	0.1156
t	-.00312***	0.00052	-5.95	0.0003	-0.00415	-0.00209

Source: own composition

The hypothesis of σ-convergence (that the dispersion of TFP across states diminishes over time) can not be rejected since the coefficient on the time variable t is significantly different from zero at 1% significance level. Our findings confirm the graphical analysis. In sum, our results imply a Sigma-convergence in the agricultural TFP across countries.

Following recent literature on the convergence (Islam, 2003) we use panel unit root tests to analyse the beta convergence. Considering the well known low power properties of univariate panel unit root tests, in this paper we employ panel unit root tests.

Before testing for panel unit root, we investigate the existence of CD in the obtained TFP scores. Following common practice in the time series convergence literature (e.g. Hernández and Ávila (2015); Sonderman, 2012), we compute the logarithm of the ratio of country specific TFP level to the average TFP level for the sample of the countries analysed. Thus the variable of interest for unit root testing (therefore for CD testing too) is the relative level of TFP (R_TFP_{it}), i.e. $R\_TFP_{it} = \ln\left(TFP_{it}/\overline{TFP_t}\right)$, where $\overline{TFP_t} = \sum_{i=1}^{N} {TFP_{it}}/{N}$, stands for the average of TFP level across countries in period t and i=1, …N stands for the number of countries.

Table 4 shows the results of CD test. This test is based on the average of pairwise correlation coefficients and under the null hypothesis of cross section independence it converges to a standard normal distribution (Moscone and Tosetti, 2009).

Table 4. Mean correlation and Pesaran (2004) CD test

Variable	CD-test	p-value	corr	abs(corr)
R_TFP_{it}	-2.1	0.036	-0.042	0.411

Source: own composition

Although the average correlation is low, the CD statistic rejects the null of cross-section independence at $p<0.05$ (Table 2). The result suggests that the second generation panel unit root test, which allows for CD, performs better in the case of convergence analysis.

Among the available second generation panel unit root tests, we choose the Pesaran (2007) test due to its favourable small sample properties. This tests show satisfactory size properties even for very small sample sizes, namely when N=T=10, and T could be small relative to N and vice versa (Pesaran, 2007).

The null hypothesis of this test is nonstationarity (i.e. no-convergence), the alternative is stationarity (i.e. convergence). We conducted the test without and with one lag and both with and without trend variable (Table 5).

Table 5. Pesaran (2007) unit root test

Specification without trend			
lags	**Zt-bar**	**p-value**	**Convergence?**
0	-2.136	0.016	Convergence
1	-0.033	0.487	No Convergence
Specification with trend			
lags	**Zt-bar**	**p-value**	**Convergence?**
0	-2.882	0.002	Convergence
1	-3.669	0	Convergence

Source: Own estimation

The results suggest that there is a convergence across countries. Without any lag both specifications confirm convergence. With one lag the specification with trend is confirmed, but teh specification without trend is rejected. As teh specification with trend is the weaker notion of convergence (Hernández and Ávila, 2015) the results are in line with the theory.

6. Discussion of the Results

We estimate relative productivity levels and decompose productivity changes for European agriculture between 2004 and 2013. Our results are partly comparable to estimations was conducted by DG AGRI[2] and the USDA[3]. DG Agri's computation shows for the period 2002-2011 0.3 per cent TFP growth and the USDA estimates for the period 2001-2005 is 2.2 per cent, for the period 2006-2010 even higher, 3.1 per cent. According to the DG AGRI's estimation the agricultural TFP growth is declining and it has practically stagnated after 2002. In contrast, USDA reports a high and increasing growth rate. Our results are broadly in line with the estimation of DG AGRI, they also show a declining trend.

Concerning the difference between the OMS and NMS, DG AGRI's estimation show a higher TFP growth for the NMS; they reports 1.6% growth per annum over the period 2002 to 2011. Our estimates for the NMS over the period form 2004-2013 is 0.33%. Although DG AGRI's estimates is higher, it is common that both our and DG AGRI's estimates show higher TFP growth in the NMS. There is only 2 countries from the NMS which can be found both in the USDA international database and in our analysis, namely Poland and Hungary. Thus a comparison concerning the difference in TFP growth in the NMS between the USDA and our estimates is not possible. For the period form 2004 to 2012 the USDA reports 0.07% TFP growth in Hungary and 1.58% in Poland. Our estimates shows for almost the same time period (2004-2013) -0.86% in Hungary and 2.02% in Poland. Our results are not consistent with the USDA estimates.

Comparable information with our results regarding TFP level can only be found in the Ball et al., 2010 paper. In this study the rank for the first, second and third countries, based on TFP level in 2002 are as follows: Netherland, Spain, Belgium. According to our results the technology leaders are similar to those reported in that study: Belgium was at the first, Netherland at the second and Denmark at the third place. Countries with the lowest TFP level in the Ball et al., 2010 study was UK, Sweden and Ireland and this rank based on our estimates

[2] The Data were taken from Matthew, 2014.

[3] http://www.ers.usda.gov/data-products/international-agricultural-productivity.aspx

are as follows: Greece, UK and Sweden. Hence, we can conclude that our results concerning TFP level are rather consistent with those results. Additionally, information about TFP level in the milk sector can be found in Cechura et al., 2014. They found that TFP is the highest in the Old Member States and the lowest in Eastern Europe. These inforamtions are also in line with our country level results.

Within the already scarce literature of productivity convergence, which looks at European countries, to the best of our knowledge, there exist only a few studies which check for cross-country TFP convergence following the first wave of eastern enlargment. Cechura et al., 2014 examined TFP convergence in the milk sector for 24 EU Member States in the period 2004 – 2011 and they found that there are no signs that poor performing farms are catching up to the best performing farms in the regions/countries. Sonderman, 2012 examined labour productivity convergence in different sectors for 12 countries in the Euro Area and found evidence of convergence. These studies are only partly comparable with our results, because of the examination of one sector (e.g. Cechura et al., 2014) ; or due to the fact that that labour productivity index was used (Sonderman, 2012).

In sum, our findings are broadly consistent with the similar empirical literature, conducted in Eu countries in the period from 2004, on TFP growth, level and convergence.

7. Conclusion

The goal of this paper is to estimate relative productivity levels and decompose productivity changes in European agriculture from 2004 to 2013. Our major findings are as follows. Firstly, that TFP in the EU slightly decreased during analysed period. Secondly, there is a huge difference between the OMS and NMS and this difference is caused mainly by the higher technological level in the OMS. The comparison of the development of TFP change and its components revealed that technological change shows a slightly decreasing trend in the OMS, whereas it has increased in the NMS. However, despite this fact, the difference between the OMS and NMS is still remarkable. These results suggest that it is essential to improve technological development in order to increase TFP both in the NMS and OMS. In the NMS it is important, because there a considerable room to improve TFP through technological development. Whereas, in the OMS it is important in order to reverse the trend of decreasing TFP. Different policies have different effects on the components of productivity change. For example, it is expected that research and development (R&D) policies have a large effect on technological change (O'Donnell, 2011b). Our results imply that supporting R&D policies could be an effective policy to increase TFP both in the OMS and NMS. The recently established EIP-Agri could be an important step in this direction. The aim of the EIP to build a bridge between science and the application of innovative approaches in practice and "reverse the recent trend of diminishing productivity gains by 2020" (EC, 2013). The presented method might be a good approach to investigate the costs and benefits of these types of programmes.

Moreover, the OSME was also lower in the NMS. Rational firms adjust their scale and input-output mix (and therefore levels of scale and mix efficiency) in response to changes in production incentives (e.g. changes in relative prices) (O'Donnell, 2011b). Our results suggest that farms in the NMS adjust their scale and scope of production less optimally than farms in the OMS. Consequently, measures that improve business environment (e.g. predictable regulatory framework, stable tax system, better access to finance and better functioning input output markets) could have a large effect on improving TFP in the NMS.

Thirdly, we investigate the TFP level and change among countries. Our results showed that the productivity level was rather stable; the rank among countries did not change significantly from 2004 to 2013. Belgium, the Netherlands and Denmark were the most productive countries, while the agricultural sector was the least productive in Latvia, Lithuania, Estonia and Slovakia. Our results also revealed that there are remarkable differences between countries.

For countries close to the technology frontier effective policy should be based on innovation, for following countries policies and institutions which facilitate imitation of technologies could also be effective. Policies should also pay major attention to learning process as key force of differences among countries TFP level, especially in the case of lagging behind regions.

In the last step of the analysis we econometrically tested the convergence of analysed countries. The results indicate that agricultural TFP converge across the European countries.

There are several further research avenues which might improve TFP estimation in the EU. Firstly, to collect variables at EU level making it possible to determine better the production environment (e.g. soil quality, more detailed climate data). The different production environments play a key role in determining the components of TFP change. Secondly, using farm level data may provide interesting new insights into the components of TFP change.

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Annex 1: Countries in the groups identified by cluster analysis and the size of the window used to estimate the technology in each region

Cluster	Countries	Window
1	AU, FR, IE, LU, SI	3
2	BE, DK, DE, NL, UK	3
3	CZ, HU, PL, SK	4
4	EE, FI, LV, LT, SE	3
5	EL, IT, PT, ES	4

Source: own composition