



New estimates of total factor productivity, technical and efficiency changes for the global agricultural economy

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Abstract

Aim of study: The accuracy of international and intertemporal comparisons of total factor productivity (TFP) growth requires the use of indicators that satisfy transitive and multiplicative properties, such as the Färe-Primont index (FPI). This paper compares the evolution of TFP in global agriculture.

Area of study: Worldwide.

Material and methods: The evolution of TFP in global agriculture was measured by the traditional Malmquist index (MI) and by the FPI, with alternative measurements of input capital.

Main results: We found a significantly lower TFP growth with the FPI. New estimates of TFP growth for 1961-2015 show that output oriented scale-mix efficiency drives TFP growth, with an important technological change between 1996 and 2000 and another in 2014. Regional comparisons reveal heterogeneous trends in efficiency, linked to institutional reforms and agricultural R&D.

Research highlights: More realistic figures and global comparisons of agricultural productivity provide a better understanding to implement better policies. Available measures of capital stock do not yield significant differences in TFP estimations, but the precise identification and estimation of the heterogeneous drivers and burdens is fundamental for boosting agricultural productivity and its benefits on global food security.

Additional key words: agricultural productivity; data envelopment analysis; Malmquist index; Färe-Primont index; agricultural capital stock

Abbreviations used: DEA (data envelopment analysis); ERS-USDA (Economic Research Service, United States Department of Agriculture); FPI (Färe-Primont index); GR (Green Revolution); IoT (internet of things); MBI (Moorsteen-Bjurek index); MI (Malmquist index); OSE (output-oriented “pure” scale efficiency); OSME (output-oriented scale-mix efficiency); R&D (Research and Development); SFA (stochastic frontier analysis); TC (technological component); TFP (efficiency component); VRS (variable returns to scale); WANA (West Asia and North Africa).

Authors’ contributions: Both authors contributed to the conception, coordination of the research activities, general and statistical analysis, interpretation of data, conclusions and drafting of the manuscript.

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Introduction

The availability of good indicators of the evolution of total factor productivity (TFP) is essential for analyzing the growth of an economy and the evolution of its supply and competitiveness. In a recent study, Le Clech & Fillat (2017a) showed that some of the most important determinants of agricultural supply dynamics are those related to sectoral productivity, such as efficiency and technology improvements. Their findings reveal that both of these factors have an important positive and highly significant effect on the international agricultural supply of grain and oilseed. Therefore, they concluded that a useful economic policy to promote the development of this sector would be one focused on stimulating technical change and efficiency improvements in this sector.

This is particularly relevant in the agricultural sector because its productivity has important consequences on food security and prices. In addition, for some poor areas, productivity growth in agriculture is essential for boosting rural incomes and reducing poverty. Furthermore, it is directly related to the use of natural resources and factor reallocation to other economic sectors. For these reasons, more realistic figures and adequate international comparisons may reveal the need to design better policies to improve agricultural productivity in some regions where its growth is meager or zero, as is the case of Europe.

On a global scale, the scarcity and quality of arable land is the main restriction to feeding an increasing population, so agricultural growth has to be driven by an increase in productivity and a sustainable intensification (IBRD/WB, 2011). Since the beginning of the twenty-first century, agricultural productivity growth has been in decline, mainly due to accelerated urbanization, improvements in diets and climate change (Popp *et al.*, 2013).

Moreover, the production of more bioenergy and other bio-based commodities are using more agricultural land. Therefore, given the rigidity of arable land expansion, the growth of agricultural and food supply has to be achieved by increasing the productivity of the land already cultivated today. Besides food security, more advances are needed in linking agricultural productivity growth to environmental impacts and in understanding its dynamic interplay with agricultural sustainability and resilience (Coomes *et al.*, 2019). For these reasons, intensification and productivity growth are fundamental pillars for the growth of agricultural yield and food security.

Many efforts have been made in recent years to improve the quality of TFP indicators and, over the last two decades,

many studies measuring TFP and conducting international comparisons on agriculture have proliferated. As Coelli & Rao (2005) indicated, this boom is due to two main reasons: the availability of new statistical information provided by the Food and Agriculture Organization (FAO) of the United Nations, and the emergence and diffusion of new techniques, such as data envelopment analysis (DEA) and the parametric technique of stochastic frontier analysis (SFA)¹. These frontier approaches have several advantages for estimating TFP indexes over other techniques, such as the price-based index numbers or the growth-accounting approach².

Until now, one of the most popular indexes for computing TFP has been the Malmquist index (MI). However, except in special cases, it is a partial measure of the productivity change, which implies that its decomposition produces estimates of technical change and technical efficiency that may be biased. The main reason for this is the existence of certain drawbacks and restrictions of the MI, mainly because it is not an exhaustive index, rather additive and multiplicative (O'Donnell, 2012).

There are diverging views on how to name the index we use as a measure of productivity change. The MI as a measure of productivity change obtains systematically biased estimates. Some of these limitations are overcome by the proposal of Bjurek (1996), who makes the key contribution of relating the MI to the Moorsteen-Bjurek index (MBI) by way of the ratio of output to input quantities. The family of MB indices becomes multiplicatively complete (O'Donnell, 2012). For more detailed information about this Moorsteen-Bjurek family of indexes we recommend Balk & Zofio (2018).

Within this family, O'Donnell (2014) proposed a particular variant, which consists in imposing a fixed base (input/output/technology) on the MBI. It becomes an additive, multiplicative and transitive index, allowing multilateral (instead of binary) comparisons. O'Donnell refers to this particular MBI as the "Färe-Primont index" (FPI) because the component output and input quantity indices were discussed in Färe & Primont (1995). However, other authors such as Diewert & Fox (2017) believed that the use of the ratio of a family of output indexes to a family of input indexes to obtain a family of productivity indexes is attributable to Bjurek (1996), so they refer to the index as the "Bjurek productivity index". Without aiming to close this debate, we use the FPI nomenclature while acknowledging that other authors might refer to it as MBI.

The aforementioned reasons justify the interest in estimating new indexes and comparing them with the traditional

¹ For a thoughtful discussion of the DEA and SFA approaches in productivity measurement see the corresponding section in Orea & Zofio (2017).

² Among the indexes based on prices can be highlighted the widely used Tornquist and Fisher indexes. The growth-accounting approach is used to estimate the world growth rates of TFP in works such as Fuglie (2012 a,b) and Avila & Evenson (2010).

ones. It is worth conducting two analyses. First, we evaluate the differences between the FPI and the MI and their sensitivity due to a change in variables. We compare the effect of considering two alternative variables of capital stock, given that some authors, such as Butzer *et al.* (2010), stressed that data on tractors, as a proxy for agricultural fixed capital, is poorer than the Capital Stock variable. Second, we offer estimates of the new TFP index for the widest sample of countries during the period 1961-2015, and of its components of technical change, efficiency change, scale efficiency and output-oriented scale-mix efficiency changes, and examine its evolution.

Material and methods

Methodology

The methodology is based on the advances developed by O'Donnell (2008, 2010, 2011a, 2012, 2014) in order to measure the TFP, based on the DEA, and calculate the components of technical change and different measures of efficiency change³. The DEA methodology has the advantage of not requiring the restrictive assumptions regarding the structure of the technology, the degree of competition in inputs and outputs markets, the use of prices as market signals or the optimizing behavior of the firm. It only requires an estimation of the production frontier which will allow us to calculate the TFP index as the basis of the decomposition into the technological index and efficiency index. TFP is defined as the relationship between outputs and inputs, which can be represented as:

$$TFP_{it} = \frac{Q_{it}}{X_{it}} \quad (1)$$

where $Q_{it} = Q(q_{it})$ and $X_{it} = X(x_{it})$ are the aggregate functions of output and inputs, respectively and are linearly homogeneous, nonnegative and no decreasing functions.

In order to estimate the production function, two approaches can be adopted, either output or input-oriented measures. In the first case, the production function is constructed from the maximum output given certain fixed factors. In the second, the costs frontier is constructed with the lowest input endowment given an output quantity. In this paper, we consider the output approach due to the particularities of the agricultural sector, which requires an important amount of "sunk capital", such as machinery and land. As Coelli & Rao (2005) noted, in the agricultural sector it is reasonable to assume the goal of maximizing

output rather than minimizing the production factors. So the distance function that represents the technology available in period t and which is output oriented can be written as:

$$D_0(x_{it}, q_{it}, t) = (q'_{it}\alpha) / (\gamma + x'_{it}\beta) \quad (2)$$

where $q(q_{1it}, \dots, q_{Jit})$ and $x_{it}(x_{1it}, \dots, x_{Kit})$ indicate the output and input vectors, for firm i and year t. The parameters α and β are nonnegative and the parameter γ captures the kind of scale returns which are assumed: $\gamma = 0$ represents constant returns to scale (CRS), $\gamma \geq 0$ represents decreasing returns to scale (DRS) and $\gamma \leq 0$ increasing returns to scale (IRS).

By means of linear optimization, the parameters which minimize $D_0(x_{it}, q_{it}, t)^{-1}$ can be estimated and the general solution is shown in equation (3):

$$D_0(x_{it}, q_{it}, t)^{-1} = \min_{\alpha, \gamma, \beta} \{ \gamma + x'_{it}\beta: \gamma l + X'\beta \geq Q'\alpha; q'_{it}\alpha = 1; \alpha \geq 0; \beta \geq 0 \} \quad (3)$$

where Q is the observed matrix of outputs ($J \times Mt$), X is the observed matrix of inputs ($K \times Mt$) and Mt is a column vector indicating the number of observations used to estimate the frontier in year t.

The specific calculations applied to the case of FPI, for both output and input distance functions, are represented by equations (4) and (5), respectively:

$$D_0(x_0, q_0, t_0)^{-1} = \min_{\alpha, \gamma, \beta} \{ \gamma + x'_0\beta: \gamma l + X'\beta \geq Q'\alpha; q'_0\alpha = 1; \alpha \geq 0; \beta \geq 0 \} \quad (4)$$

$$D_1(x_0, q_0, t_0)^{-1} = \max_{\phi, \delta, \eta} \{ q'_0\phi - \delta: Q'\phi \leq \delta l + X'\eta; x'_0\eta = 1; \phi \geq 0; \eta \geq 0 \} \quad (5)$$

The linear optimization of equations (4) and (5) yields the parameters $\alpha_0, \beta_0, \gamma_0, \phi_0, \delta_0$, and η_0 and t_0 defines the observations that are used to estimate the representative frontier. The aggregate functions used to compute the FPI are:

$$Q(q) = q'p_0^* \quad \text{with} \quad p_0^* \equiv \partial D_0(x_0, q_0, t_0) / \partial q_0 = \alpha_0 / (\gamma_0 + x'_0\beta_0) \quad (6)$$

$$X(x) = x'w_0^* \quad \text{with} \quad w_0^* \equiv \partial D_1(x_0, q_0, t_0) / \partial x_0 = \eta_0 / (q'_0\phi_0 - \delta_0) \quad (7)$$

The FPI, as well as the MI, can be decomposed into two components: the technological component (TC) and the efficiency component (EC), as follows:

$$TFP_{it} = TC_t \cdot EC_{it} \quad (8)$$

Moreover, the calculation of each index is obtained from:

$$TC_t = \max_i Q_{it} / X_{it} \quad (9)$$

$$EC_{it} = TFP_{it} / TC_t \quad (10)$$

³ We have used the program DPIN 3.0 for the calculations, the performance of which is explained in O'Donnell (2011b).

The technological component measures a shift of the production frontier during a period. It is calculated by identifying the economic unit i that shows the maximum level of TFP for a given period t . The efficiency change measures a movement of the economic unit towards (or away from) the production frontier, which means an improvement (or worsening) in the efficient use of the production factors.

Some other measures of efficiency can be calculated. In this paper we are interested in analyzing two of them: the output-oriented “pure” scale efficiency (OSE), which measures the difference between TFP at a technically γ efficient point and the maximum TFP that is possible with fixed mixes of input and output (but allowing the levels to vary), and the output-oriented scale-mix efficiency (OSME), that accounts for productivity shortfalls associated with diseconomies of both scale and scope. In other words, scale-mix efficiency is a measure of the improvement in productivity obtained by moving from a technically efficient point to a point of maximum productivity.⁴

For the OSE index it is necessary first to estimate the output-oriented technical efficiency (OTE) assuming variable returns to scale (VRS) and CRS. These indexes are defined as follows:

$$OTE_{it} = Q_{it} / \bar{Q}_{it} \leq 1 \quad (11)$$

$$OSE_{it} = OTE_{it}^{VRS} / OTE_{it}^{CRS} \leq 1 \quad (12)$$

$$OSME_{it} = \bar{Q}_{it} / X_{it} / TC_t \leq 1 \quad (13)$$

where $\bar{Q}_{it} = Q_{it} / D_0(x_{it}, q_{it}, t)$ is the maximum aggregate output that can be produced by i in period t while holding its input vector and its output mix fixed.

Data, variables and sample

Dimensionality is always present in non-parametric estimation, implying that working in smaller dimensions tends to provide better estimates of the frontier (Daraio & Simar, 2007). For this reason, our estimation is conducted with the most aggregated version of each variable. We use gross agricultural output for each country at constant 2004-2006 average international prices, in thousands of dollars. As inputs we include: a) *Labor*: number of economically active adults in agriculture; b) *Land*: total agricultural land

in hectares of “rainfed cropland equivalents” c) *Feed*: total metabolizable energy (ME) in animal feed from all sources, in 1000 Mcal; d) *Fertilizer*: amount of metric tons of N, P₂O₅, K₂O fertilizer consumption; e) *Livestock*: total livestock capital on farms expressed in “cattle equivalents” based on relative size and feeding requirements; and f) *Machinery*: total stock of farm machinery in “40-CV tractor equivalents” (CV=metric horse power), aggregating the number of 2-wheel tractors, 4-wheel tractors, and combine-harvesters and threshers. All data are drawn from the most recent update of the international agricultural productivity database from the Economic Research Service, United States Department of Agriculture (ERS-USDA) (<https://www.ers.usda.gov/data-products/international-agricultural-productivity/>).

We consider the variable Capital Stock as an alternative to Livestock+Machinery. It is the sum of the individual physical assets and includes Land Development + Livestock (fixed assets and inventory) + Machinery & Equipment + Plantation Crops + Structures for Livestock. All data from the net capital stock dataset in agriculture from FAOSTATS.⁵

The complete data provided by ERS-USDA enable estimates to be made for almost 200 countries. However, it is well known that nonparametric DEA is vulnerable to potential outliers and measurement error (Simar & Wilson, 2013). And even when there are new techniques to detect outliers for the DEA technique, the decision on how many units to exclude is still arbitrary (Boyd *et al.*, 2016). The trade-off between working with the widest sample and minimizing the bias for outliers prompted us to select all countries with at least 0.15% of total world gross agricultural output in 2015 and this sample accounts for 95% of it. In this way, we obtain a highly representative sample that includes the key future players in agricultural production.

According to the two alternative proxies for agricultural capital, we obtain two samples. The first is used to compare the estimates of both the MI and FPI, both with the Capital Stock and Machinery+Livestock variables.

The reason is that the FAOSTATS Capital Stock database groups certain countries together, such as those of the former USSR, for the whole period. This yields a sample (Sample 1) with 64 countries/regions from 1975 to 2007.

Table S1 [suppl] lists the included countries. The second sample (Sample 2) is from the ERS-USDA dataset and is used to study the agricultural TFP dynamics from 1961 to 2015. It is longer and also identifies individual countries

⁴ There are no output-oriented mix efficiency (OME) measures in this decomposition because the aggregator functions are proportional to the output and input distance functions (See O’Donnell, 2012 and 2014). For a more detailed discussion about these indexes, see O’Donnell (2018).

⁵ Food and Agriculture Organization of the United Nations. FAOSTAT (2012). Capital Stock (Dataset). <http://data.fao.org/ref/f297ce49-6f72-4ffd-bbcb-2b300bd0bc4d.html?version=1.0> [Latest update: 07 Mar 2014. Accessed 22 Aug 2019].

from the former USSR. Applying the same “95%” rule, we obtain a sample of 73 countries/regions, which are listed in Table S2 [suppl].

Results

Malmquist and Färe-Primont comparison

Our first goal is to compare the MI and FPI estimates using two alternative variables of capital stock. Hence, we have two models for each index: Model 1, involving the *Output, Labor, Land, Feed, Fertilizer and Capital Stock* variables, and Model 2, involving the *Output, Labor, Land, Feed, Fertilizer, Livestock and Machinery* variables. All estimations were conducted assuming VRS and no technical regress.

Table 1 shows the estimates (weighted annual mean change) and their annual geometric mean rate of growth of the TFP: 1.42% for the MI model 1 and 1.34% for the MI model 2, while the FPI yields are 1.26% and 1.17% for models 1 and 2, respectively, which are much lower rates.

The cumulative change of TFP in 2007 is 1.595 and 1.550 for the MI, models 1 and 2 respectively, while the FPI change is 1.512 and 1.468 for models 1 and 2 (Fig. 1). This result indicates that, for both models, the MI is higher than the FPI and could be interpreted as an overestimation of the growth of TFP in agriculture.

To test whether the differences between the four estimates are statistically significant, we have conducted two paired sample tests on the weighted annual mean change series reported in Table 1 and on the cumulative series shown in Figure 1. One is the classical t-test and the other is the Wilcoxon signed-rank test. The general null hypothesis H_0 for the t-test is that the mean of the difference is equal to 0, and for the Wilcoxon test the median of the difference is equal to 0. A rejection of the null hypothesis means that both indicators are significantly different, and its acceptance means that the accuracy of both indexes is similar. Table 2 presents the results for the eight null hypotheses tested and it is important to note that both tests obtain the same results in terms of the acceptance of the null hypothesis.

The first and second H_0 relate MI model 1 with MI model 2, and FPI model 1 with FPI model 2 respectively. In both cases, the H_0 of equality is strongly accepted, indicating that the effect of a change in one of the input-variables, such as capital, does not produce any significant bias for either MI or FPI. However, when the cumulative series are evaluated (H_0 5 and 6) only the FPI obtains similar results and the MI is sensitive to the proxy for capital.

H_0 3, 4, 7 and 8 relate MI to its FPI counterpart. The rejection of H_0 3 and 7 indicates that the estimations of the MI and FPI are different when the capital stock in model is considered. H_0 is not rejected, indicating that MI and FPI yield statistically the same aggregate results when the traditional Machinery and Livestock capital variable is considered. Given that this has been the most common

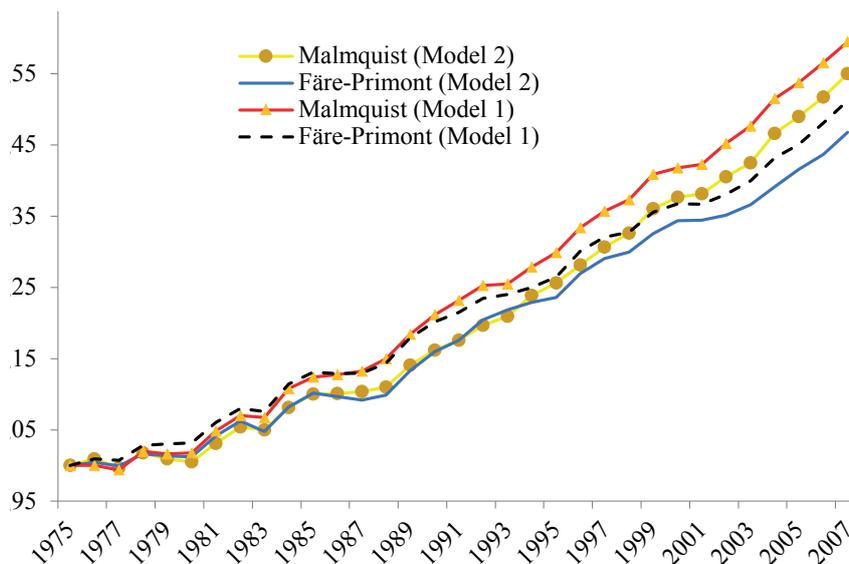


Figure 1. Cumulative TFP indexes.

Table 1. Malmquist and Färe-Primont TFP indexes. Weighted annual mean change 1975-2007.

| Years | MI Model 1 | MI Model 2 | FPI Model 1 | FPI Model 2 |
|--------------------------|------------|------------|-------------|-------------|
| 1975 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| 1976 | 1.0002 | 1.0093 | 1.0092 | 1.0042 |
| 1977 | 0.9935 | 0.9878 | 0.9982 | 0.9951 |
| 1978 | 1.0265 | 1.0206 | 1.0205 | 1.0172 |
| 1979 | 0.9962 | 0.9921 | 1.0019 | 0.9973 |
| 1980 | 1.0018 | 0.9960 | 1.0017 | 0.9980 |
| 1981 | 1.0300 | 1.0257 | 1.0278 | 1.0293 |
| 1982 | 1.0206 | 1.0219 | 1.0187 | 1.0201 |
| 1983 | 0.9972 | 0.9966 | 0.9957 | 0.9863 |
| 1984 | 1.0385 | 1.0296 | 1.0356 | 1.0326 |
| 1985 | 1.0142 | 1.0173 | 1.0152 | 1.0182 |
| 1986 | 1.0028 | 1.0010 | 0.9984 | 0.9954 |
| 1987 | 1.0047 | 1.0023 | 1.0003 | 0.9956 |
| 1988 | 1.0156 | 1.0060 | 1.0125 | 1.0062 |
| 1989 | 1.0295 | 1.0276 | 1.0311 | 1.0317 |
| 1990 | 1.0233 | 1.0183 | 1.0190 | 1.0231 |
| 1991 | 1.0165 | 1.0117 | 1.0112 | 1.0139 |
| 1992 | 1.0172 | 1.0178 | 1.0164 | 1.0247 |
| 1993 | 1.0016 | 1.0108 | 1.0045 | 1.0115 |
| 1994 | 1.0189 | 1.0242 | 1.0078 | 1.0088 |
| 1995 | 1.0160 | 1.0142 | 1.0114 | 1.0057 |
| 1996 | 1.0270 | 1.0202 | 1.0289 | 1.0267 |
| 1997 | 1.0171 | 1.0196 | 1.0153 | 1.0169 |
| 1998 | 1.0117 | 1.0148 | 1.0051 | 1.0066 |
| 1999 | 1.0258 | 1.0260 | 1.0212 | 1.0201 |
| 2000 | 1.0066 | 1.0115 | 1.0087 | 1.0136 |
| 2001 | 1.0035 | 1.0039 | 0.9997 | 1.0008 |
| 2002 | 1.0206 | 1.0169 | 1.0104 | 1.0050 |
| 2003 | 1.0167 | 1.0139 | 1.0134 | 1.0111 |
| 2004 | 1.0264 | 1.0293 | 1.0228 | 1.0184 |
| 2005 | 1.0146 | 1.0162 | 1.0132 | 1.0173 |
| 2006 | 1.0183 | 1.0180 | 1.0209 | 1.0149 |
| 2007 | 1.0187 | 1.0216 | 1.0212 | 1.0216 |
| Cumulative | 1.595 | 1.550 | 1.512 | 1.468 |
| Geometric mean of growth | 1.42% | 1.34% | 1.26% | 1.17% |

Table 2. Paired sample T-test and Wilcoxon signed-rank test. 1976-2007.

| Null hypothesis | T-Test | | Wilcoxon | |
|--|---------|---------|----------|--------|
| | T (abs) | p-value | W | 1.0042 |
| Annual change series | | | | |
| 1) μ MI-Model 1 - μ MI-Model 2 = 0 | 1.102 | 0.279 | 325 | 0.254 |
| 2) μ FPI-Model 1 - μ FPI-Model 2 = 0 | 1.244 | 0.223 | 339 | 0.164 |
| 3) μ MI-Model 1 - μ FPI-Model 1 = 0 | 2.207 | 0.035 | 379 | 0.032 |
| 4) μ MI-Model 2 - μ FPI-Model 2 = 0 | 1.633 | 0.112 | 316 | 0.186 |
| Cummulative series | | | | |
| 5) μ MI-Model 1 - μ MI-Model 2 = 0 | 10.657 | 0.000 | 522 | 0.000 |
| 6) μ FPI-Model 1 - μ FPI-Model 2 = 0 | 0.824 | 0.416 | 203 | 0.262 |
| 7) μ MI-Model 1 - μ FPI-Model 1 = 0 | 4.075 | 0.000 | 429 | 0.001 |
| 8) μ MI-Model 2 - μ FPI-Model 2 = 0 | 0.508 | 0.615 | 203 | 0.262 |

practice in this kind of estimation, it would mean that the estimations in all existing aggregate studies carried out with MI could be still relatively valid even in spite of the potential overestimation of TFP that the MI presents.

Finally, it is remarkable that our results do not find any significant difference caused by the use of alternative proxies for the agricultural capital (capital stock vs. Machinery and Livestock) in the FPI results. By accepting the hypothesis by Butzer *et al.* (2010) that the Capital Stock variable is a better measure of agricultural capital stock than tractors, we can consider that the Machinery and Livestock composed variable reported by ERS-USDA is a good proxy for the agricultural capital stock variable.⁶

Färe-Primont results

In this section, we offer the estimates of the FPI for the longest possible period according to the available information, which is for a sample of 73 countries that covers 95% of world agricultural production for 2015 and for the

period 1961-2015. This sample (Sample 2) is detailed in Table S2 [suppl]. The estimations were conducted assuming VRS and no technical regress.⁷ Table 3 summarizes the estimates with the weighted average annual growth for the whole period and three sub-periods and Fig. 2 represents their cumulative evolution. Our estimates indicate that the weighted (geometric mean) annual growth rate of the TFP from 1961-2015 is only 1.03%. Although this reflects relative poor dynamics, it is interesting to observe some differences between periods.

Following Pingali (2012), we distinguish two main periods, the first Green Revolution (GR), between 1966 and 1985, and the post-Green Revolution over the following two decades (1986-2005). In addition, we consider a third period, which we could call the “High Tech Revolution” which is characterized by the irruption of the so-called internet of things (IoT) into the agricultural industry. TFP gains during the first GR were the smallest of these three periods. In addition, the greatest driver for this period was the improvement of OSME with null

Table 3. Weighted geometric mean annual growth. TFP, TC, OSME and OSE.

| Period | TFP | TC | OSME | OSE |
|-----------|-------|-------|-------|-------|
| 1966-1985 | 0.71% | 0.00% | 0.74% | 0.17% |
| 1986-2005 | 1.15% | 0.68% | 0.29% | 0.48% |
| 2006-2015 | 1.07% | 0.49% | 0.53% | 0.27% |

TFP: total factor productivity. TC: technological component. OSME: output-oriented scale-mix efficiency. OSE: output-oriented “pure” scale efficiency).

⁶ All these results are somewhat different from those obtained by Le Clech & Fillat (2017b), where a different sample and assumptions are used in order to compare them with other studies.

⁷ The estimations are available on request. The supplementary material of this paper includes the summary data that form the basis of the tables and figures in this section (Table S3 [suppl])

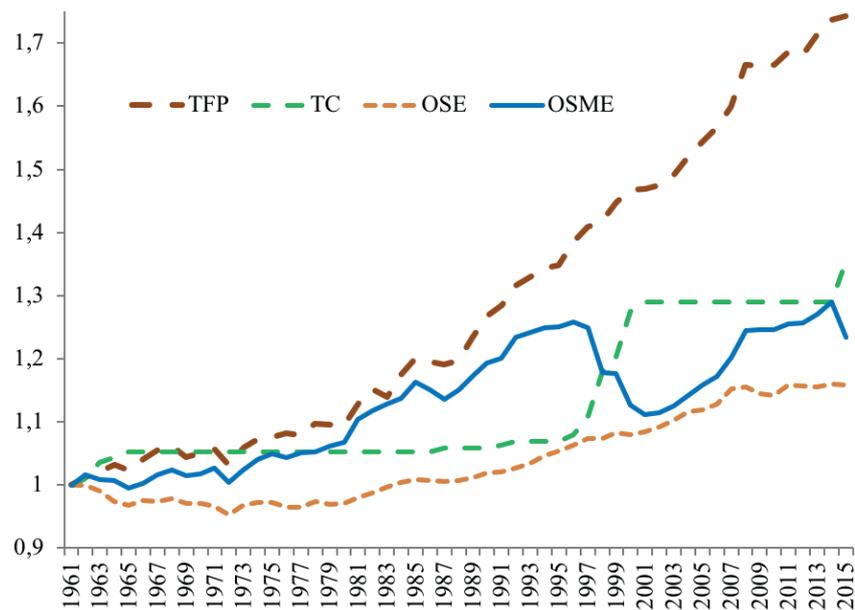


Figure 2. Cumulative TFP, TC, OTE, OSE and OSME indexes.

impact of technology and a small growth in OSE. These facts are congruent with new findings that indicate that, in spite of the rapid success of GR on rice and wheat, it took much longer for GR to be extended to other crops (Gollin *et al.*, 2018). According to these authors, the rate of adoption and the number of new crop varieties released increased in the 1980s and 1990s and the acceleration seems to have continued to the present day. In other words, the effects of GR on a global level are evident only from the post-GR period. In addition, GR initially depended on the use of fertilizers, pesticides and irrigation to create conditions in which high-yielding modern varieties could thrive, which could explain the zero growth of TC and the relevance of OSME in our estimations for the first period since this kind of efficiency indicates possible improvements in productivity due to changes in input structure.

The agricultural economy experienced an important boom during the post-GR period, in which two stages can be identified. The first was led by efficiency improvements, likely due to the opening up of the world economy which occurred from the late 1980s and intensified during the 1990s. The second started in the mid-1990s and was led mainly by technological improvements. This technological wave may be explained basically by the diffusion of the use of direct seeding and the new developments in GM. The upsurge observed from 1996 to 2000 is remarkable. In this period, globalization and the inter-

national transfer of technology were essential factors in promoting the commercial spread of GM crops in developing countries (Pingali & Terri, 2005).

Comparing the first GR with the post-GR period, it is important to note the differences in scale efficiency that constituted one of the major drivers for the second period. This result confirms that GR technology was scale-neutral. As Patel (2013, p. 19) stated: "First, then, is the claim, found in Mosley (2002), Birner & Resnick (2010) and Hazell *et al.* (2010) that the Green Revolution technology was scale neutral, with divisible inputs, and therefore of benefit to both smallholders and larger farm owners". On the other hand, the post-GR period was characterized by land concentration processes and the implementation of several genetic improvements in crops. These changes focused mostly on producing high-yielding varieties, which decrease in time to maturity and produce an increase in cropping intensity, allowing an additional harvest per year in some regions.

During the third period, TC remained unchanged until 2014, when a new leap occurred. It is probably due to a contagious effect of the diffusion of the "new digital-revolution" in agriculture, which provided new opportunities for the smarter use of agricultural resources. This included remote sensing and spatial mapping technologies, cell phones and other information and communication technologies that can contribute to the smarter application of water, fertilizers and other inputs.

Throughout the last period, both technology and OSME also played an important role. Scale efficiency played a less important role than during the previous period.

Some regional comparisons

By region, West Asia and North Africa (WANA) show average rates of 1.66%, above the world average, followed by Asia, Oceania, North America and Latin America, with rates of 1.17%, 1.24%, 1.14% and 1.11% respectively. Below the world average are Sub-Saharan Africa, the Former Soviet countries and Europe with rates of 0.94% 0.68% and 0.45% respectively. Fig. 3 shows this evolution.

According to their growth in efficiency (Fig. 4 and Table S3 [suppl]), the ranking is the same, from WANA's

efficiency growth of 1.09% to even small or negative rates for the Former Soviet countries and Europe, with a growth rate in efficiency of 0.11% and -0.11% respectively. In all regions, from the mid-1990s to 2001 there was a recession in efficiency and a subsequent recovery.

West Asia and North Africa's relatively high TFP growth is driven by technical efficiency. Nin *et al.* (2017) attributed the boost to efficiency in the early 1990s to the one-time effect of the policy reforms. Later, new technologies and investments, such as irrigation, improved agricultural practices and the development of high-value crops drove TFP, undermined by a significant population pressure on labor markets. Egypt dominated TFP growth, Iran and Morocco showed moderate growth, while Turkey's had been declining from the 1990s due to efficiency losses (Ozden, 2014; Abukari *et al.*, 2016; Nin *et al.*, 2017).

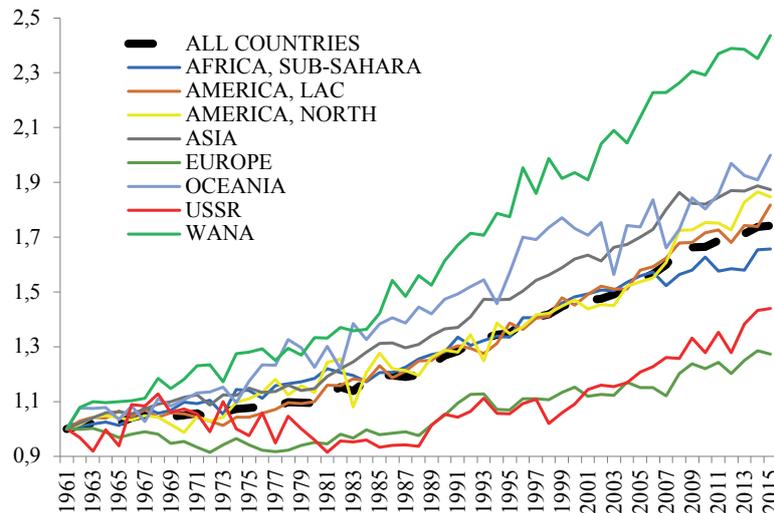


Figure 3. Cumulative TFP indexes by regions.

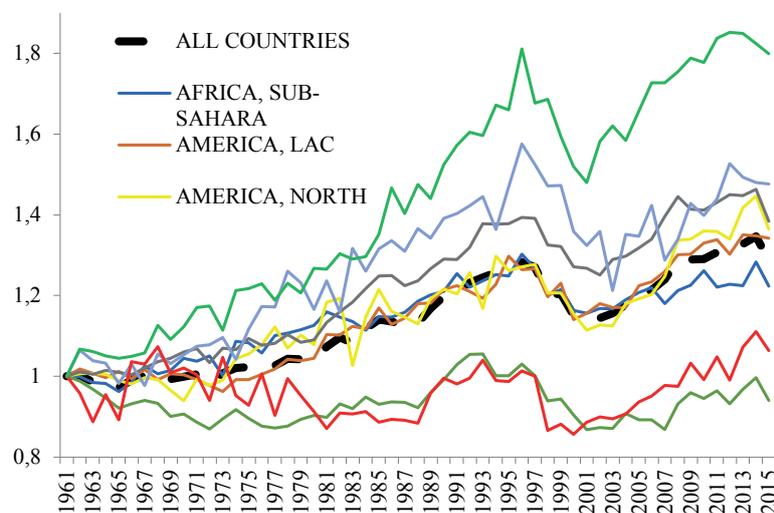


Figure 4. Cumulative efficiency indexes by regions.

In Asia, TFP increased gradually throughout the period, with a boost in 1980 and a slight slump in the early 1990s. The index captures the incidence of countries with high productivity growth, such as China, and countries with low productivity growth but a significant weight, such as India. Throughout the 1970s and 1980s, India invested in new green technologies and infrastructures. However, instability due to climatic shocks affected the TFP trend. The boost in the 1980 reflects China's high agricultural TFP growth; with improved water control, access to fertilizers and other inputs, investment in agricultural R&D and, since the 1990s, direct seeding and other capital intensive advances. The slight slump in the 1990s reflects the reduction in agricultural efficiency in India and the stagnation of productivity in Indonesia from 1992 to the recovery after the Asian financial crisis. Since 2002, the TFP of certain Chinese cereals has stagnated or declined due to inappropriate management practices related to fertilizers, soil and water, evolving institutional structures, unstable research spending or a boom in horticulture and livestock over other crops. Recent advances in TFP growth reflect the Chinese strategy for a sustainable intensification of production, diversification towards high-value agriculture and progress in productivity in India, the return to an agriculture-first development strategy in Indonesia or the re-greening program in Vietnam (Ludena, 2010; IBRD/WB, 2011; Jin *et al.*, 2012; Fan *et al.*, 2012; Fuglie, 2012c; Sing & Pal, 2012).

In Oceania, TFP grew strongly from the 1970s, driven by efficiency. This growth was reversed in the late 1990s. TFP growth has been larger in Australia than in New Zealand and in crops than in livestock. Although scale economies had been important, this trend reversed because of an increasing use of purchased inputs in cropping, the stagnation of public investment in agricultural research since the 1970s and the run of poor seasons, particularly for the period 2001-2007 (Mullen, 2012).

In North America there was an increasing trend in TFP growth, which was slightly slower in the 1980s. In 1994 efficiency declined but recovered after 2003. Some authors have found a slowdown in the agricultural productivity of the United States in the 1980s and 1990s (Alston *et al.*, 2012; Ball *et al.* 2013) and in that of Canada (Veeman & Gray, 2012; Darku *et al.*, 2016), attributed to the previous slowdown of total spending on agricultural R&D. In the late 1990s efficiency dropped and TFP growth was driven by technological change, probably related to the GR. The recovery of efficiency from 2003 is consistent with the recent evidence of agricultural intensification in capital and the positive impact of public and private research activity, such as that conducted on crop seeds, biotechnology, crop protection chemicals, fertilizers, farm machinery, animal health, animal genetics and animal nutrition (Ball *et al.*,

2013; Wang *et al.*, 2013). In Canada, scale economies from a few large livestock farms boosted TFP, along with technical change, which is the main driver in crops.

In Sub-Saharan Africa, TFP growth was not robust in the region until the 1980s but there have been successful experiences. Ethiopia and Kenya have developed programs for sustainable soil and water conservation, early warning systems and increased value added adapted to producer's priorities; Niger and Burkina Faso are implementing projects of this type. In South Africa, an increase in the average farm size and the production of higher-value commodities, drove productivity but, since the late 1980s, productivity growth has slowed down. Botswana suffers from marked differences between commercial and traditional farmers, while assistance to agriculture after independence in Ghana is a clear driver of TFP (IBRD/WB, 2011; Fuglie, 2012c; Liebenberg & Pardey, 2012; Block, 2016).

Latin America has experienced sustained TFP growth since the 1980s and, since, the 1960s in Argentina. Until the 1980s efficiency losses undermined TFP growth, although since 2001 all countries have experienced a positive trend. In Argentina, scale and scope economies as well as technological change have driven TFP. In the early 1990s, trade liberalization, the creation of Mercosur and currency convertibility favored imports of inputs, machinery and irrigation equipment, with crops growing faster than livestock. After a collapse at the end of 2001, the highly favorable conditions in world markets encouraged a strong recovery from 2002 to 2007, although subsequent policies seem to be "against agriculture". Brazil has sustained exceptionally high TFP growth rates since the 1980s and the benefits from research since the mid-1990s. The TFP in Chile increased from 1961 to 2011, with slowdowns in the 1980s and in 1996; in Paraguay it decreased until the 1990s and Uruguay shows slower growth (Ludena, 2010; Fuglie, 2012c; Lence, 2012; Lema, 2015).

In the Former Soviet countries, TFP and efficiency growth paths started with the green revolution and the radical reforms in the 1990s. This trend was fueled by the spillovers from Foreign Direct Investment in the Baltic States and the rich Central European countries, and in the poorest members since 2000. After 1998, the increased liquidity in Russia was invested in agriculture and the food industry and promoted productivity growth. In Kazakhstan and Ukraine, reforms were implemented slowly, and productivity regressed in the poor Transcaucasian and Central Asian countries because of the shift toward individual farming (Fuglie, 2012c; Swinnen *et al.*, 2012).

Finally, TFP growth in Europe practically stagnated until 2007, with efficiency losses in most of the period. Innovation is the effective policy for countries at the technological frontier but technological changes are scarce.

Efficiency is the driver of TFP, which is negative in Germany, Finland or Slovenia. The regional structural break in 1996 and the decline and recovery of efficiency is also documented in the UK (Piesse & Thirtle, 2012; Domanska *et al.*, 2014; Baráth & Fertó, 2017).

To sum up, there have been important advances in TFP growth, with a structural change in the mid-1990s and heterogeneous trends in efficiency. Institutional reforms and agricultural R&D have been drivers of productivity. Recent literature suggests technological and ecosystem-based approaches to leverage agricultural TFP (Coomes *et al.*, 2019).

Discussion

We have carried out new estimations of the TFP in the agricultural sector based on the most recent advances made by O'Donnell (2014) that allow multilateral and international comparisons. The comparison of these two indexes shows that the MI seems to be sensitive to changes in variables while FPI provides more robust results. However, given the evidence obtained in the comparison between MI and FPI for model 2, their difference was not significant. Therefore, the estimates presented by all past aggregated studies carried out with MI could be still relatively valid in spite of the potential overestimation of TFP.

Regarding the difference in the proxies for capital stock variables and based on the FPI results, the evidence does not show any important differences between the results obtained from the two variables of agricultural capital stock (Capital Stock *vs.* Machinery+Livestock). In this respect, we can state that the Machinery+Livestock variables reported by ERS-USDA are good proxies for the agricultural capital stock variable.

For the general analysis of the global results, we have distinguished three main periods, the first Green Revolution (1966-1985), the post-Green Revolution (1986-2005) and a third period we have called the "High Tech Revolution" (2006-2015). Our findings show that the first GR was the period with the slowest growth, with null impact of technology and the improvement of OSME as the main driver. This coincides with new findings that indicate that it took much longer for GR to be extended to other crops and across the world. Observing the TC leap in the mid-1990s, we can conclude that the rate of adoption and the number of new crop varieties released due to the GR increased at the end of the 1980s and throughout the 1990s until the present day. In other words, technological impacts of the GR on a global level are evident only from the

post-GR period. In addition, the zero growth of TC and the relevance of OSME could be explained by the change in the input structure to create the conditions in which high-yielding modern varieties could thrive.

The post-GR period reveals an important boom for the agricultural economy, in which two stages can be identified. The first is led by efficiency improvements, likely driven by the world economic opening-up from the late 1980s and during the 1990s. The second began in the mid-1990s, led mainly by technological improvements and largely explained by the diffusion of the use of direct seeding and the new developments in GM. The remarkable technological change between 1996 and 2000 reflects the effect of globalization and the international transfer of technology in promoting GM crops in developing countries. While scale was neutral during the first GR, scale efficiency was one of the major drivers during the post-GR. This second period was characterized by a land concentration process and the implementation of several genetic improvements in crops that allowed an additional harvest per year in some regions, which increased scale efficiency.

The third period was characterized by a stagnation of TC, which remained unchanged up to 2014, when a new upsurge occurred, probably facilitated by the initial diffusion in agriculture of the "new digital-revolution", which provided new opportunities for the smarter use of agricultural resources. Throughout this period, both technical and scale efficiency also played an important role, although scale efficiency was more important in the previous period. These new IoT technologies are expected to have an important impact on agriculture industry. Some authors, such as Pingali (2012), have pointed out that the adaptation of precision agriculture techniques for developing country smallholder agriculture conditions could have significant global public good benefits. However, it remains to be seen whether this new technological leap will be as important as the one occurring between 1990 and 2000.

The important advances in TFP have been heterogeneous by region, with higher TFP and efficiency growth in West Asia and North Africa, Asia, Oceania and North America; growth occurred later or stagnated in Sub-Saharan Africa, Former Soviet countries and Europe. Efficiency and productivity trends have been closely linked to scale economies in Oceania, North America and Latin America; the main drivers in West Asia and North Africa and India have been infrastructures and new technologies; reforms have been fundamental in West Asia and North Africa and the Former Soviet countries; finally, a boost in agricultural R&D has propelled TFP in China while an R&D slowdown has undermined it in North America.

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