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International Agricultural Productivity Growth: is there a consistent pattern across the methods?

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1 Introduction

Projections of future productivity growth rates are an essential input for many tasks (Ludena et al., 2007). For example, they have important implications for the supply-side response to the growing global food demands. Yet solid projections of regional and global productivity growth have proven elusive. This is due, in no small part, to the difficulty of measuring historical total factor productivity growth (TFP).

Despite this long tradition of applied research on global agricultural productivity patterns, the stock of results provides a very mixed picture of long-run trends and displays considerable variation across countries, regions and studies (Evenson and Fuglie, 2009; Fulginiti and Perin, 1999). There is no clear consensus on such important issues as whether global agricultural TFP growth has been slowing or accelerating, or the magnitude of agricultural TFP growth in Sub-Saharan Africa in recent decades. Headey et al. (2010), summarize the current state of the art by saying that *"Agricultural productivity and its determinants are clearly important but have not always been well measured or well understood"*.

Why is there so little consensus after 70 years of research on global agricultural productivity? Table 1, which provides an overview of a representative list of studies from the last two decades on global TFP growth, highlights some of the key potential sources of variability in results.

Data sources and study periods are the first candidates for concern. Most of studies used FAOSTAT annual data (FAO, 2010) on agricultural outputs and inputs since 1961. This dataset is perhaps the best available for producing internationally comparable agricultural productivity estimate, and its development is considered to be one of the driving forces behind the expansion of empirical literature on global TFP growth over the last two decades (Coelli and Rao, 2005). Still, there are some acknowledged deficiencies in the data, specifically for measuring TFP growth rates. This has lead researchers to augment the core FAO data with additional information ('FAO plus' in the Table 1) in an attempt to account, for example, for quality differences in input data (e.g. Wiebe at al., 2000; Graig et al., 1997; Evenson and Fuglie, 2009) or for appropriate measures of the agricultural capital stock (von Cramon-Taubadel et al., 2009). Hence, differences in the data, combined with differences in the study periods considered most likely explain some of the variability in results.

A second source of variability stems from the empirical modeling and estimation techniques employed. According to Fulginiti and Perin (1999), "…*Consistent average rates mask substantial inconsistencies from country to country. …. These comparisons do not inspire much confidence that the parametric and nonparametric approaches are measuring the same phenomenon*". In a recent paper, Headey at al. (2010) estimate global TFP growth using SFA and DEA approaches and contrast the resulting estimates. Without reference to formal tests, the authors prefer the SFA results. These results, however, contradict common belief/expectations among agricultural economists. For example, the average annual TFP growth in the Sub-Saharan Africa region is found to be greater than 2% using the SFA approach. This is higher than many experts who are familiar with African agriculture expect. von Cramon-Taubadel et al. (2009) contrast TFP growth estimates using DEA and robust partial frontier (m-order) approaches. They reach conclusions that are similar to those of Fulginiti and Perin (1999); despite some consistency in the results there are large discrepancies for Sub-Saharan Africa as well as North Africa and the Middle East regions. A further example is provided by

Fuglie (2008) and Evenson and Fuglie (2009) who employ an Index numbers approach to measure agricultural TFP. Contrary to the past empirical evidence of a general slowdown in global productivity growth, their results suggest that global agricultural TFP has accelerated since 1980.

Table 1 Studies on international agricultural productivity growth

Study	*Estimation method*	*Countries*	*Study period*	*Model: # outputs - # inputs*	*data source*
Fulginiti and Perrin (1993)	CD	18 LDC	1961-85	1 - 5	FAO plus
Fulginiti and Perrin (1997)	DEA	18 LDC	1961-85	1 - 5	FAO plus
Craig et al. (1997)	Part. Productivity measures	98	1961-90	-	FAO plus
Lusigi and Thirtle (1997)	DEA	47 Af.	1961-91	1 - 5	FAO, WATIVIEW
Fulginiti and Perrin (1998)	DEA&CD	18 LDC	1961-85	1 – 5	FAO plus
Arnade (1998)	DEA	70	1961-93		
Fulginiti and Perrin (1999)	DEA&CD	18 LDC	1961-85	1 – 5	FAO plus
Martin and Mitra (1999)	Translog	50	1967-92	1 – 3	World Bank
Wiebe et al (2000)	Part. Productivity measures	110	1967-97	1 - 5	FAO plus
Chavas (2001)	DEA	12	1960-94		
Ball et al. (2001)	Fisher (EKS)	10 DC	1973-93		Eurostat plus
Suhariyanto et al (2001)	DEA	65 As./Af.	1961-96		
Suhariyanto and Thirtle (2001)	sequential DEA	18 Asia	1965-96	1 – 5	WATIVIEW, FAO
Trueblood and Coggins (2003)	DEA	115	1961-91	1 – 5	FAO
Nin et al. (2003)	sequential DEA	20LDC	1961-94	2 - 6	FAO
Bravo-Ortega and Lederman (2004)	Translog	77	1961-00	1 – 5	FAO
Coelli and Rao (2005)	DEA	93	1980-00	2 – 6	FAO
Ludena et al. (2007)	directional DEA	116	1961-01	3 - 9	FAO plus
Fuglie (2008)	Solow-type growth accounting method	171	1961-06	2 – 5	FAO plus
von Cramon-Taubadel et al. (2009)	DEA and m-order	111	1970-07	1 - 4; 2 - 6	FAO plus
Evenson and Fuglie (2009)	Solow-type growth accounting method	156	1970-05	2- 5	FAO plus
Headeyet al. (2010)	DEA and SFA	88	1970-01	2 - 5	FAO plus

Source: own presentation and Coelli and Rao (2005)

Further potential sources of variability in TFP estimates that have been acknowledged in recent papers (e.g. Headey et al., 2010; von Cramon et al., 2009) include: i) the dimensionality of DEA models; ii) measurement errors in the data; iii) contraction of the frontier in DEA models; iv) unrealistic implicit input value shares in DEA models; v) outliers; vi) production function forms; vii) aggregation; and viii) the imputation of output and input value shares in the Index numbers approach.

The objective of this study is to make a contribution to finding common ground among different estimates of global TFP growth. We apply a wide range of estimation methods to a consistent and comprehensive dataset. The dataset and modeling methods account for past deficiencies and critiques. Estimation methods include the most recent advances in efficiency and productivity analysis (e.g. the robust partial frontiers developed by Cazals et al., 2002) as well as conventional methods (DEA, FDH, SFA, Index numbers).

In the last part of the paper we study the patterns of productivity growth estimates. To this end, we test whether the agricultural productivity growth is accelerating or decelerating using the range of estimates produced according to different methods as outlined above.

2 Methodology and Data

2.1 Discussion of the output and input data

The dataset of the study contains 184 countries and the time frame begins in 1975 and extends to 2007. For output, FAO publishes data on production of crops and livestock and aggregates these into a production index using a common set of commodity prices based on the 1999–2001 period.
For inputs, we mainly use FAOSTAT database. Inputs are divided into six categories. Farm labor is the total economically active population (males and females) in agriculture. Fertilizer is the amount of major inorganic nutrients applied to agricultural land annually, measured as metric tons of N, P2O5, and K2O equivalents. The rest four are the categories of the agricultural capital stock (ACS). Comprehensive data of the ACS in the study is based on physical inventories contained in the FAOSTAT database which are available for essentially all countries over several decades, but which only cover a relatively narrow set of fixed assets in farming. They are i) land (arable land, permanent crops, irrigation land), ii) livestock (cattle, buffaloes, sheep, goats, pigs, horses, camels, mules and donkeys, poultry), iii) machinery (tractors, harvesters milking machines, hand tools), iv) structures (for animals, for poultry).
To convert physical inventories into asset values, we use the 1995 unit asset prices that were compiled by the FAO (2002). These were drawn from a number of sources such as country investment project reports prepared by and for FAO, FAOSTAT data on purchase prices of means of production such as tractors, and unit trade values. For details on these unit prices and other aspects of the estimation, the reader is referred to FAO (2001a) and von Cramon et al. (2009). Using constant prices to arrive at ACS costs allows us to overcome some notorious deficiencies in the data. For example accounting for a quality of the land turned out to be an important ingredient for measuring international TFP growth rates (e.g. Fugli, 2008; Craig et al, 1997). Another issue is omission of horsepower of tractors as the input variable (e.g. see Coelli and Rao, 2005). In these two cases the unit land and machinery prices will reflect the quality and power differences in corresponding ACS categories.

2.2 Discussion of the methods for TFP growth measurement

Total Factor Productivity (TFP) is defined as the ratio of total output to total inputs. The direct way to calculate the changes of TFP over the time is to use the index number approach. In a multi-output and multi-input setting it might be calculated, for instance, via a conventional Divisia index, defined as

(1) $$\dot{TFP} = \sum_{k}^{K} s_k \frac{dx_k}{x_k} - \sum_{m}^{M} r_m \frac{dy_m}{y_m}$$

Here, s_k denotes the cost share of input x_k, and r_m denotes the revenue share of output y_m. The key challenge of this method is to collect a representative cost and revenue shares for most countries. If fixed revenue and cost shares are used over a long period, this could potentially lead to the ‘index number bias’. Using this method Evenson and Fuglie (2009) and Fuglie (2008) with region-wise fixed revenue and cost shares, contrary to the past empirical evidence of a general slowdown in global productivity growth, find that global agricultural TFP has

accelerated since 1980. In our application we collect significantly disaggregated and country- and time-specific data on cost shares for the countries in LAC, Asia and Africa regions as in Avila and Evenson (2010). For the rest countries we use region-wise cost shares (Method 2: Divisia index w/var. shares) as in Evenson and Fuglie (2009). For comparison we also generate Divisia TFP growth index using region-wise fixed factor shares (Method 1: Divisia index w/const. shares).

Malmquist TFP index is the alternative measure of TFP growth. It is, perhaps, the most frequently used method over the last two decades and it is defined via the output distance functions (e.g., see Färe et a., 1994). The main advantage of the Malmquist index is that it does not require the data on input and output prices. It's another important property for our application is that under the constant returns to scale technology the Malmquist index simplifies to a Tornquist-type index (Caves et. al, 1982), which is comparable to the Divisia index in eq. (1) with non-constant output and input cost shares.

The distance functions in Malmquist TFP index are defined relative to the reference technology frontier that requires an appropriate methodology to estimate/construct. There are two approaches to deal with it, namely non-parametric and parametric. DEA is probably the most often used method in the family of non-parametric methods. The main advantages of DEA are well documented in the literature and require no further detailed discussion (see e.g. Daraio and Simar, 2007; Coelli et al, 2005). However, the disadvantages of the 'conventional' DEA (Method 3: Conventional DEA) certainly need a brief discussion at least for two reasons. Ignoring them affects the resulting frontier estimate and makes the resulting TFP growth estimates unreliable. The disadvantages of the conventional DEA gave rise to completely new methods or modified versions of DEA (they are discussed below) that are also used in TFP growth analysis and lead to variability of resulting TFP growth estimates.

The resulting optimal weights or 'shadow prices' of inputs and outputs in the equivalent dual formulation of the distance function (e.g., see Kuosmanen et al, 2004) and consequently implicit cost and revenue shares, might significantly differ from prior knowledge or conventional views, this might question the reliability of the resulting TFP growth estimates. For instance, Coelli and Rao (2005) report a zero mean shadow value share for land for USA and Mexico. Conventional way to overcome this is to impose the bounds on the value shares, leading to so-called 'restricted' DEA (Method 5: Restrictive DEA). As in the Divisia index case above, we introduce country- and time-specific bounds on cost shares for the countries in LAC, Asia and Africa regions as in Avila and Evenson (2010). For the rest countries we use region-wise cost shares as in Evenson and Fuglie (2009).

Nin et al. (2003) raises the next problem. He points out that DEA-based TFP growth results often show contractions of the frontier over long period of time, which might look questionable in light of the technology adoption and diffusion expectations. Nin et al. (2003) propose to use a 'cumulative/sequential technology' DEA (Method 4: Sequantial DEA) approach that precludes the possibility of the technology recession. This modified DEA approach makes use of all the input-output data on all countries available for all time points up to the period of estimation. Method 6 (Sequential & Restrictive DEA) in our toolkit combines the advantages of the two methods described above.

The main limitations of the conventional and the three modified DEA methods being acknowledged in the literature are the curse of dimensionality and sensitivity to outliers (Daraio and Simar, 2007; p.48). As we estimate a relatively high

dimensional model, these problems are potentially acute in our application. For instance, before the breakdown of the Soviet Block (Soviet Union, Yugoslavia SFR, and Czechoslovakia) in the early 90s, we could consider estimating DEA model with 2 outputs and 6 inputs on 163 observations. Since the DEA estimator converges at rate of $n^{-2/(n+m+1)}$, it is not difficult to show that this nonparametric estimator is roughly equivalent to that of a corresponding fully parametric model estimated with only 10 observations (see details in Daraio and Simar, 2007; p.153). Clearly, estimating such a model makes resulting frontier and distance function estimates (and thus TFP growth) unreliable. To overcome this problem we aggregate some of the inputs to decrease the dimensionality of the DEA models to 2 outputs and 3 inputs.

As an alternative, partial or so-called robust frontiers can be estimated based on the order-m expected maximum output frontier (Method 7: Order-m) and order-α (Method 8: Order-alpha) quantile-type frontier (Daraio and Simar, 2007; p.65). The main idea of the order-m method is to estimate a frontier which does not envelop all the data points. The idea behind order-α method is to determine the frontier by fixing fist the probability (1- α) of observing points above this order-α frontier. These partial frontiers have nice statistical properties ($\sqrt{n}$ consistency and asymptotic normality), so they do not suffer from the curse of dimensionality problem shared by DEA models. Also the order-α frontiers are more robust to extremes that the order-m (Daraio and Simar, 2007; p.74). TFP growth rates we estimate as in Wheelock and Wilson (2003) and Wheelock and Wilson (2009).

The basic drawback of all the above non-parametric methods discussed above is that they do not allow for noise. This might be a very important restriction in the context of country-level data. Although FAOSTAT database is perhaps the best available for producing internationally comparable agricultural productivity estimate, still it is widely maintained that it might be strongly flawed in some cases especially for developing countries (e.g. see a short discussion in Headey et al., 2010). The family of SFA (parametric) models allows for the noise in the data. Using flexible form of the production function (e.g. translog) the SFA, however, is limited by strong assumptions on the error and inefficiency terms. In our application we estimate the heteroscedactic 'Error Components Frontier' model of Battese and Coelli (1992) on a pooled dataset. The translog stochastic distance function is constructed as in Brümmer et al (2002) and we compare two approaches to model the technical change. In the first case we model it as a 'standard time trend' model (Method 9: SFA w/trend) with a constant technical change rate. Alternatively, we replace the time trend component with a 'general index of technical change'. This specification mimics in a sense a nonparametric approach above since incorporating the time dummies allows us to construct a time specific frontier (Method 10: SFA w/general index of tech. change). The technical change is much less restricted in this case. For the details of the time trend versus general index technical change models refer to Baltagi and Griffin (1988). Parameters of the distance functions in the parametric and non-parametric models are restricted to the CRS case.

3 Results and Discussion

To begin with we applied a semi-automatic methodology proposed by Simar (2003) to detect the most extreme observations. Overall, we identified and dropped from

the sample only three outlying observations. They are Romania (in 1977) and Thailand (in 1982 and 1985).

Table 2 Summary statistics, 1975-2007

	mean	Std	min	max
Output1: livestock, 1000 I$	2840894.44	9134554.23	592.00	120801200.00
Output2: crop, 1000 I$	4823642.54	17143304.61	32.00	265647000.00
Input1: land, 1000 I$	12566.47	40765.50	0.25	362324.11
Input2: livestock, 1000 I$	5608.71	15038.29	0.23	146593.24
Input3: machinery, 1000 I$	3717.77	15081.28	0.13	185666.99
Input4: structures, 1000 I$	1111.48	4719.63	0.12	75665.88
Input5: fertilizers, 1000 t	829914.72	3382786.69	3.00	65104026.00
Input6: labor, 1000	7101.09	40001.27	1.00	499018.00

Source: own presentation

Table 3 TFP growth in different regions of the world according to different specifications and estimation techniques (average annual rate of TFP growth in %)

Method, Specification (# of outputs = p, # of inputs = q)	SSA, devd	SSA, devg	LAC	N. America	N.Asia, devd	China	R.Asia	W.Europe	CEEC	FSU	M.East & N. Africa	Oceania	India	World
Divisia Index: const shares p = 2, q = 3	1.92 (4)	1.1 (13)	2.2 (2)	1.3 (11)	1.9 (5)	2.37 (1)	1.73 (8)	1.7 (9)	1.18 (12)	1.45 (10)	2 (3)	1.85 (7)	1.85 (6)	1.9
Divisia Index: var. shares p = 2, q = 3	1.72 (7)	1.38 (10)	2.28 (2)	1.3 (12)	1.63 (9)	2.7 (1)	2.03 (3)	1.7 (8)	1.11 (13)	1.34 (11)	2 (4)	1.8 (6)	1.87 (5)	1.98
Conv. DEA p = 2, q = 3	1.88 (7)	3.1 (1)	1.43 (11)	2.41 (5)	0.13 (13)	2.24 (6)	1.86 (8)	2.54 (4)	1.44 (10)	2.64 (2)	2.54 (3)	0.95 (12)	1.8 (9)	2.29
Seq. DEA p = 2, q = 3	1.63 (10)	2.4 (4)	2.25 (6)	2.76 (1)	0.43 (13)	2.39 (5)	1.97 (7)	2.55 (2)	1.2 (11)	1.91 (8)	2.53 (3)	1.18 (12)	1.89 (9)	2.34
Restr. DEA p = 2, q = 3	1.79 (9)	1.84 (8)	2.33 (2)	1.87 (7)	0.76 (12)	2.27 (3)	2.07 (4)	1.96 (5)	1.69 (10)	1.95 (6)	2.53 (1)	0.53 (13)	1.66 (11)	2.09
Seq. Restr. DEA p = 2, q = 3	1.81 (7)	1.77 (8)	2.19 (2)	1.91 (5)	0.94 (12)	1.97 (3)	1.85 (6)	1.96 (4)	1.61 (9)	1.49 (10)	2.31 (1)	0.56 (13)	1.48 (11)	1.97
Order-m p = 2, q = 6	2.9 (3)	2.05 (9)	2.19 (8)	2.48 (6)	1.45 (12)	3.02 (2)	1.54 (10)	3.27 (1)	2.52 (4)	2.48 (7)	2.5 (5)	1.38 (13)	1.47 (11)	2.66
Order-alpha p = 2, q = 6	2.34 (4)	2.3 (6)	1.81 (10)	2.78 (3)	1.13 (13)	3.09 (2)	1.31 (12)	3.39 (1)	2.21 (7)	2.33 (5)	2.1 (9)	1.61 (11)	2.14 (8)	2.65
SFA: trend p = 2, q = 6	1.05 (3)	0.17 (12)	0.96 (5)	0.95 (6)	-0.32 (13)	1.84 (1)	0.67 (9)	0.61 (10)	0.95 (7)	0.97 (4)	0.8 (8)	0.51 (11)	1.1 (2)	1.04
SFA: gen.tc.ind p = 2, q = 6	0.84 (10)	3.33 (4)	3.19 (5)	1.64 (8)	-0.31 (13)	3.57 (1)	3.5 (2)	1.11 (9)	0.35 (12)	0.39 (11)	3.44 (3)	2.96 (6)	2.61 (7)	2.63

Source: Authors' estimates

Notes: ranks in brackets; SSA, dvg (Sub-Sahara Africa, developing), SSA, dvd (Sub-Sahara Africa, developed), N.America (North America), North Asia, dvd (North Asia developed), R. Asia (Rest of Asia), W.Europe (Western Europe), CEEC (Central and Eastern European Countries), FSU (Former Soviet Union 12 countries), M.East&N.Africa (Middle East and North Africa), LAC (Latin America and Caribbean)

Table 3 compares the regional aggregates (using output weights) of TFP growth estimates from different models (for the same input-output data and the same 184

countries, see Table 2 for summary statistics[1]). In general the global average TFP growth varies from 1.9% (Divisia index with const shares) to above 2.6% (partial frontiers and SFA with general index of technical change). The ranking of the regions across the methods does not reveal a consistent pattern. For instance, the SSA (devg) region lags far behind according to the Index numbers and SFA with trend approaches, i.e. 13th and 12th (out of 13) in the lists with 1.1% and 0.17% of average annual TFP growth respectively. However, it ranks high according to the conventional DEA model and SFA with general index of technical change model, i.e. 1st and 4th with 3.1% and 3.33% of average annual TFP growth respectively. The only region that ranks consistently across parametric and non-parametric models is North Asia (devd). It is in the end of the list with even negative average TFP growth in SFA models (about -0.3%), and it is also in the end across nonparametric models (12th or 13th). China in most of the cases is on top of the list with 1.84-3.57% average annual TFP growth.
Rank-correlation (spearman) statistics of the individual (country- and year-specific) TFP growth rates in the Table 4 confirms the lack of association in the patterns of TFP growth estimates across the methods. In most of cases the individual results from different estimation methods show no statistically significant correlation.

Table 4 Rank-correlation (spearman) statistics of the individual disaggregated TFP growth indexes

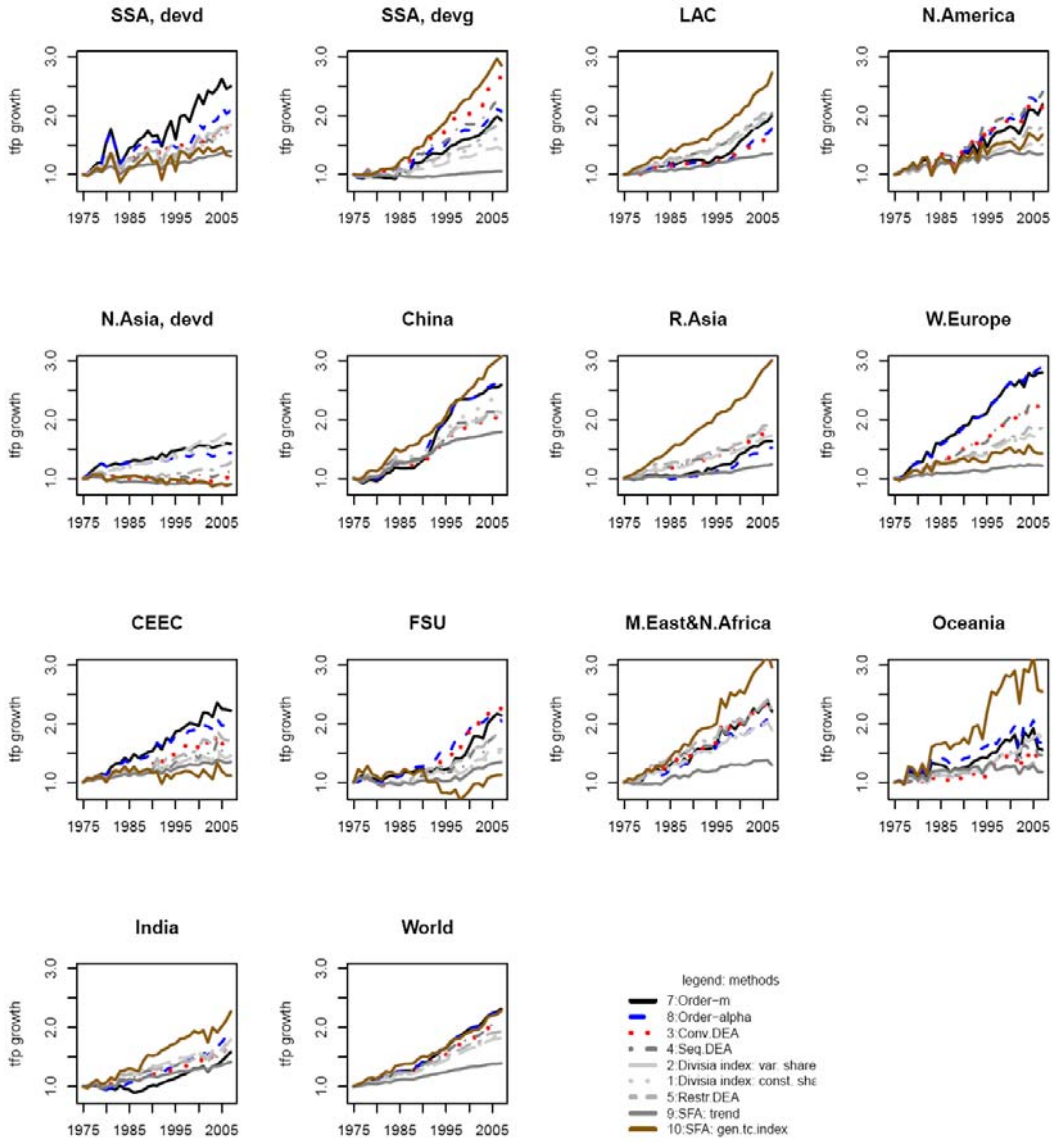
Specification	Divisia Index: const	Divisia Index	Conv. DEA	Seq. DEA	Restr. DEA	Seq. Restr. DEA	Order-m	Order-alpha	SFA: trend	SFA: gen.tc.ind
Divisia Index: const shares	***	0.03	0.03	0.03	0.02	0.01	0.00	0.01	-0.01	0.00
Divisia Index	0.03	***	0.03	0.04	0.02	0.02	0.02	0.01	0.00	-0.01
Conv. DEA	0.07	0.04	***	0.03	0.04	0.02	0.02	0.01	0.02	0.00
Seq. DEA	0.07	0.02	0.05	***	0.03	0.04	0.01	0.01	0.01	0.01
Restr. DEA	0.28	0.12	0.02	0.08	***	0.02	0.02	0.01	0.02	0.00
Seq. Restr. DEA	0.35	0.31	0.30	0.02	0.19	***	0.03	0.02	0.00	0.03
Order-m	0.99	0.32	0.23	0.36	0.11	0.10	***	0.03	0.01	0.00
Order-alpha	0.72	0.60	0.34	0.60	0.69	0.17	0.06	***	0.03	0.02
SFA: trend	0.53	0.79	0.29	0.51	0.13	0.95	0.43	0.04	***	0.04
SFA: gen.tc.ind	0.93	0.51	0.89	0.62	0.78	0.07	0.79	0.16	0.01	***

Source: Authors' estimates
Notes: upper diagonal part contains correlation coefficients; lower diagonal contains corresponding p-values

Figure 1 gives a hint to the answer whether tfp growth is accelerating or decelerating. Similar to the discussion above, the cumulative regional TFP growth patterns are very heterogeneous and complex. They vary from one method to another and from one region to another. For instance, the cumulative TFP growth patterns for the North Asia (devd) region demonstrate negative as well as positive trend. However, overall it looks like the time series of cumulative TFP growth are trending linearly upward, except for China and FSU where the trend looks nonlinear.

[1] Table with groupings and countries involved in the analysis is available from the authors upon request

Figure 1 Cumulative TFP growth rates resulting from different methods, 1975-2007



Source: Authors' estimates; Notes: ranks in brackets; SSA, dvg (Sub-Sahara Africa, developing), SSA, dvd (Sub-Sahara Africa, developed), N.America (North America), North Asia, dvd (North Asia developed), R. Asia (Rest of Asia), W.Europe (Western Europe), CEEC (Central and Eastern European Countries), FSU (Former Soviet Union 12 countries), M.East&N.Africa (Middle East and North Africa), , LAC (Latin America and Caribbean)

To give a more specific answer to this, for each method we test how the distributions of TFP growth estimates evolve over the time. For this we use Kolmogorov-Smirnov (K-S) test on the equality of distributions. For each method we perform year-wise comparisons of TFP indexes and tested which of the two compared distributions is stochastically greater (acceleration of TFP growth) or smaller (deceleration of TFP growth) at 5% significant level. For each method we performed 480 comparisons and looked at whether we have similar patterns of

"significance shots" for each particular year across the methods. A careful look at these demonstrates a quite incidental/random (w/o a pattern) and sparse (not many methods) character of 'significance shots'[2]. Based on this we can conclude that there has been no significant change (i.e. no acceleration and deceleration) in the international agricultural TFP growth patterns. As we already observed it early in the Figure 1, the cumulative international TFP growth is trending linearly upwards.

Conclusions

Despite a long tradition of applied research on global agricultural productivity patterns, the stock of results provides a very mixed picture of long-run trends and displays considerable variation across countries, regions and studies. Moreover, there is no clear consensus on such important issues as whether global agricultural TFP growth has been slowing or accelerating, or the magnitude of agricultural TFP growth in Sub-Saharan Africa in recent decades.

In this paper we make a contribution to finding a common ground among the global TFP growth patterns resulting from different estimation techniques. We apply a wide range of estimation methods to a consistent and comprehensive panel of countries over 1975 to 2007. The core of the dataset is the FAO dataset on agriculture, adjusted for some notorious deficiencies and critiques. Estimation methods include the most recent advances in efficiency and productivity analysis as well as the conventional methods.

The results demonstrate that there are large variations in TFP growth rates across the regions and methods. The global average TFP growth varies from 1.9% to above 2.6% over 1975 to 2007. The ranking of the regions across the methods does not reveal a consistent pattern. Rank-correlation statistics of the individual country-wise TFP growth rates confirms the lack of association in the patterns of TFP growth estimates across the methods.

Looking at the region-wise cumulative patters of TFP growth and by comparing statistically country-and year-wise distributions of the individual TFP growth rates resulting from different methods we could not infer about a consistent patterns of acceleration or deceleration of the global TFP growth rates among the methods.

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[2] Tables with the results are available from the authors upon request

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