Components of agricultural productivity change: Replication of US evidence and extension to the EU

Author(s):
Wimmer, Stefan; Dakpo, K. Hervé

Publication date:
2023-09

Permanent link:
https://doi.org/10.3929/ethz-b-000614452

Originally published in:
Applied Economic Perspectives and Policy 45(3), https://doi.org/10.1002/aepp.13377

Received: 14 January 2022 | Accepted: 25 April 2023

DOI: 10.1002/aepp.13377

FEATURED ARTICLE

AAEA Agricultural & Applied Economics Association WILEY

Components of agricultural productivity change: Replication of US evidence and extension to the EU

Stefan Wimmer[1] | **K Hervé Dakpo**[1,2]

[1]Agricultural Economics and Policy Group, ETH Zürich, Zürich, Switzerland

[2]Université Paris-Saclay, INRAE, AgroParisTech, PSAE, Palaiseau, France

Correspondence
Stefan Wimmer, Agricultural Economics and Policy Group, ETH Zürich, Zürich, Switzerland.
Email: swimmer@ethz.ch

Editor in charge: Robert Finger

Abstract

Increasing agricultural productivity is a policy priority in many countries. O'Donnell (*Am. J. Agric. Econ.* 94(4): 873–890, 2012) decomposed productivity change in US agriculture using a Lowe total factor productivity (TFP) index. We replicate the original study, assess its robustness to alternative TFP indices, and extend the analysis to EU agriculture. We consistently find that productivity growth in US agriculture is mainly driven by technical progress. In EU agriculture, TFP growth is less pronounced, and both technical change and efficiency change contribute to productivity changes. In both US and EU agriculture, the magnitude of measured productivity change varies across indices, highlighting the need to rely on multiple indices for robust policy recommendations.

KEYWORDS

agricultural productivity, index measurement, productivity decomposition, technical change, total factor productivity

JEL CLASSIFICATION

D24, O47, Q10

Producing sufficient food for a growing world population with changing dietary demands is a major challenge for agriculture (FAO, 2017). At the same time, environmental pressures require minimizing the use of limited resources such as land or chemicals. Improvements in agricultural productivity enable farmers to produce more outputs with the same amount of inputs, or to use fewer inputs to produce the same amount of output, and is therefore a policy priority in many countries. In the past decades, global agriculture achieved large productivity gains, but recent evidence suggests that productivity growth is slowing down in industrialized countries (Fuglie, 2015, 2018).

The evaluation and design of public policies aiming at productivity growth require an appropriate measurement of productivity as well as the identification of the sources of productivity change, such as technical change or efficiency change. In this paper, we replicate O'Donnell (2012b), who decomposed productivity change in US agriculture (1960–2004) into several economically meaningful measures, and extend the analysis to agriculture in the European Union (EU) (2000–2019). To improve comparability, we additionally measure productivity in the EU and the United States using a global agricultural production data set from 1961 to 2020.

The preferred productivity measure for sectors using multiple inputs to produce multiple outputs is total factor productivity (TFP). O'Donnell (2011) refutes widely used TFP indices, such as Fisher or traditional Malmquist indices, as they violate the transitivity property, challenging their suitability to make multitemporal and multilateral comparisons of TFP. In the productivity context, transitivity ensures that comparing productivity of two firms directly yields the same index number as comparing two firms indirectly through another firm, and hence allows for consistent comparisons involving more than two observations. In an influential paper, O'Donnell (2012b) suggested an index number decomposition method using a TFP index attributed to Lowe (1823) that satisfies the transitivity property, by using sample average prices as fixed weights to aggregate outputs and inputs.[1] The empirical results in O'Donnell (2012b) suggest that technical change was the primary driver of US agricultural productivity growth in the period 1960–2004, and that technical efficiency was higher and more stable than scale-mix efficiency.

The present study aims to replicate these results, compare the results to alternative productivity indices, and extend the analysis to EU agriculture. In this paper, we focus on indices that satisfy the transitivity property besides other basic axioms from index number theory as explained in detail in O'Donnell (2016). First, we replicate the original findings using the additive Lowe index and US state-level data provided by the US Department of Agriculture (USDA). Second, we test the robustness of the results to another additive index that uses averages of shadow prices (estimated using data envelopment analysis) instead of observed prices as weights (hereinafter called "A-DEA"), a multiplicative index that uses estimated elasticities based on stochastic frontier analysis (hereinafter called "M-SFA"), and a global Malmquist index proposed by Pastor and Lovell (2005). We also test the robustness with respect to the returns to scale assumption. Third, we extend the analysis to EU agriculture using official production data from Eurostat (Eurostat, 2023) over the period 2000–2020, which provide country-level information about the same agricultural outputs and inputs as contained in the US state-level data. Finally, since the periods covered by the US and EU data sets differ, we employ the International Agricultural Productivity (IAP) data set, also provided by USDA, which covers the years 1961–2020 and is the globally most complete data on agricultural output and inputs.

Besides O'Donnell (2012b), several studies have decomposed TFP change in US agriculture into individual components (e.g., Andersen et al., 2012; Capalbo, 1988; Mugera et al., 2016; O'Donnell, 2014; Plastina & Lence, 2018). Similar to the study to be replicated, Capalbo (1988), Andersen et al. (2012), O'Donnell (2014), and Plastina and Lence (2018) all use state-level data and consistently find that technical progress is the major driver of US productivity growth.

Mugera et al. (2016) find the same result using farm-level data from Kansas. In EU agriculture, studies on TFP growth and its components are more limited. The existing analyses mostly rely on selected country studies and single farm types, such as Cuesta (2000) for Spanish dairy farms; Brümmer et al. (2002) for dairy farms in Germany, Poland, and the Netherlands; or Sipiläinen (2007) for Finnish dairy farms. Using country-level data from EU member states, Baráth and Fertő (2017) found that TFP has slightly decreased in EU agriculture between 2004 and 2013, with varying importance of technical change and efficiency change.

Our replication study contributes to the understanding of agricultural productivity changes by estimating and decomposing TFP changes in US and EU agriculture, which together account for nearly 20% of worldwide agricultural gross production in 2018 (FAO, 2020). We thereby add to the limited evidence on TFP in European agriculture. Employing various TFP measurement techniques including nonparametric and parametric approaches, we evaluate the sensitivity of the results in the original article by O'Donnell (2012b) to alternative choices and methods. The results show that the original results can be successfully reproduced and that its main results are very robust. Overall, we find that TFP growth in US agriculture has been mainly driven by technical progress (encompassing technological progress and environmental change), while TFP growth in EU agriculture has been less pronounced, and TFP change has been driven by both technical and efficiency changes.

In the following section, we summarize the methods used to measure productivity change and its components. Next, we present the replication of the original study: We shortly describe the data used in O'Donnell (2012b), describe the replicated results, and provide robustness checks. Subsequently, we extends the analysis to EU agriculture. The final section discusses the results, offers policy implications, and concludes.

METHODS

This section summarizes the aggregate quantity-price framework developed by O'Donnell (2011, 2012a, 2012b). In this framework, $\mathbf{x}_{it} \in \mathbb{R}_+^M$ and $\mathbf{q}_{it} \in \mathbb{R}_+^N$ are vectors of input and output quantities for unit i in year t, and the corresponding input and output price vectors are denoted by $\mathbf{w}_{it} \in \mathbb{R}_+^M$ and $\mathbf{p}_{it} \in \mathbb{R}_+^N$. Aggregate input and aggregate output are defined as $X_{it} = X(\mathbf{x}_{it})$ and $Q_{it} = Q(\mathbf{q}_{it})$, where $Q(.)$ and $X(.)$ are non-negative, non-decreasing, and linearly homogeneous aggregator functions. TFP is given by the ratio of aggregate output and aggregate input (e.g., Jorgenson & Griliches, 1967):

$$TFP_{it} = \frac{Q_{it}}{X_{it}} \tag{1}$$

Comparing TFP of unit i in period t with TFP of firm h in period s yields the TFP index

$$TFPI_{hsit} = \frac{TFP_{it}}{TFP_{hs}} = \frac{QI_{hsit}}{XI_{hsit}}\ , \tag{2}$$

where $QI_{hsit} = Q_{it}/Q_{hs}$ and $XI_{hsit} = X_{it}/X_{hs}$ are output and input quantity indices. With implicit aggregate output prices P_{it} and input prices W_{it}, the profitability index is

$$PROFI_{hsit} = \frac{PROF_{it}}{PROF_{hs}} = TTI_{hsit} \times TFPI_{hsit} \ , \tag{3}$$

where the terms of trade index $TTI_{hsit} = PI_{hsit}/WI_{hsit}$ measures implicit changes in output prices relative to input prices. O'Donnell (2012a) shows that any TFP index that consists of aggregate input and output quantities as in Equation (2) can be decomposed into measures of technical change and TFP efficiency change, i.e.,

$$TFPI_{hsit} = \frac{TFP_{it}}{TFP_{hs}} = \frac{TFP_t^*}{TFP_s^*} \times \frac{TFPE_{it}}{TFPE_{hs}} \ , \tag{4}$$

where TFP_t^* denotes the maximum level of TFP in period t, and $TFPE_{it} = TFP_{it}/TFP_t^*$ is ratio of observed TFP over maximum TFP.

In this paper, we view the production technology as a technique for transforming inputs into outputs, and aim to decompose productivity change into technical change (encompassing technological progress, i.e., the discovery of new techniques, and environmental change) as well as efficiency change including changes in technical efficiency (i.e., ability to use the right technique or to implement the right technique properly). The employed indices and their decompositions are explained in the following.

Additive productivity indices (Lowe and A-DEA)

The Lowe TFP index is obtained by using the linear aggregator functions $Q(\mathbf{q}_{it}) \propto \mathbf{p}_0'\mathbf{q}_{it}$ and $X(\mathbf{x}_{it}) \propto \mathbf{w}_0'\mathbf{x}_{it}$, where $\mathbf{p}_0$ and $\mathbf{w}_0$ are pre-determined unit- and time-invariant reference prices directly obtained from the data (e.g., sample average prices):

$$TFPI_{hsit}^{Lowe} = \frac{\mathbf{p}_0'\mathbf{q}_{it}}{\mathbf{p}_0'\mathbf{q}_{hs}} \times \frac{\mathbf{w}_0'\mathbf{x}_{hs}}{\mathbf{w}_0'\mathbf{x}_{it}} \tag{5}$$

Another additive TFP index is obtained by using average estimated shadow prices $\mathbf{p}_0^*$ and $\mathbf{w}_0^*$ as weights, i.e. $Q(\mathbf{q}_{it}) \propto \mathbf{p}_0^{*'}\mathbf{q}_{it}$ and $X(\mathbf{x}_{it}) \propto \mathbf{w}_0^{*'}\mathbf{x}_{it}$. We obtain these shadow prices from the estimation of Shephard (1953) output and input distance functions (e.g., Färe & Grosskopf, 1990; Grosskopf et al., 1995) using data envelopment analysis (DEA) and hence call the corresponding additive TFP index "A-DEA".[2] We then decompose these two additive indices into economically meaningful components using DEA techniques. For a detailed description of these methods, we refer to the original paper by O'Donnell (2012b). In line with the original paper, we compute a measure for technical change (i.e., technological progress and environmental change) as well as the following TFP efficiency components:

- The Farrell (1957) output-oriented measure of technical efficiency, that is, the difference between observed and maximum TFP when input levels and output mixes are fixed (hereinafter "OTE").
- The conventional measure of output-oriented scale efficiency (e.g., Balk, 2001), measuring the difference in TFP between at a technical efficient point and the maximum TFP when holding output and input mixes fixed (hereinafter "OSE").

- Pure output-oriented mix efficiency, measuring the difference in TFP between a technically efficient point and a point with TFP-maximizing output mix (hereinafter "OME").
- Output-oriented scale-mix efficiency, measuring the difference in TFP between a technical efficient point and the maximum possible TFP (hereinafter "OSME").

The presence of scale efficiency measures allows for the possibility that units can exploit economies of scale by increasing or decreasing production, given variable returns to scale. However, with aggregate regional or country-level data at hand, this idea may not always be sensible because size in such an analysis does not represent the size of an individual decision-making unit but rather the size of the sector. Hence, it is common to assume constant returns to scale with aggregate regional or country-level data (e.g., Chambers et al., 2020; Coelli & Rao, 2005). For this reason, we will provide a robustness check with respect to the returns-to-scale assumption below.

Multiplicative productivity index (M-SFA)

As a robustness check to the (nonparametric) additive indices, we estimate a multiplicative productivity index based on parametric output distance functions following Njuki et al. (2018) and Dakpo et al. (2021). The output distance function is estimated using stochastic frontier analysis (Aigner et al., 1977; Meeusen & van Den Broeck, 1977), and hence we call the corresponding multiplicative TFP index "M-SFA". We assume that the technology can be approximated by the following (linearized) Cobb–Douglas functional form:

$$-\ln q_{1it} = \alpha_0 + \sum_{n=2}^{N} \alpha_n \ln \frac{q_{nit}}{q_{1it}} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \sum_{j=1}^{J} \sum_{h=1}^{T^*} \gamma_{hj} R_{ji} S_{ht} t + \nu_{it} + u_{it} \tag{6}$$

The greek letters α, β, and γ in Equation (6) are parameters to be estimated. In case of constant returns to scale, we normalize the dependent variable and all input variables by one common input variable so that $\sum_{k=1}^{K} \beta_k = -1$. The error term consists of the random fluctuation term ν_{it} following a normal distribution, and of the technical inefficiency term u_{it} following a half-normal distribution, and both error term components are assumed to be independently distributed from each other and from the regressors. R_{ji} is a binary variable that is one if unit i belongs to region j and zero otherwise, and S_{ht} is a binary variable that is one if time period t lies within the hth 5-year period an zero otherwise. T^* indicates the number of 5-year time periods. The interaction of the time trend t with these binary variables allows the rate of technical change—which captures shifts in the production frontier that may be due to changes in environmental variables and/or technological progress—to vary every fifth year and across regions, in an attempt to mirror the assumptions in the DEA approach in O'Donnell (2012b). We then use the estimated parameters from Equation (6) to construct a multiplicative TFP index of the form

$$TFPI_{hsit}^{M-SFA} = \left[\prod_{n=1}^{N} \left(\frac{q_{nit}}{q_{nhs}} \right)^{\alpha_n} \right] \times \left[\prod_{k=1}^{K} \left(\frac{x_{khs}}{x_{kit}} \right)^{\lambda_k} \right], \tag{7}$$

where $\lambda_k = \beta_k / \sum_{j=1}^{K} \beta_j$ and $\alpha_1 = 1 - \sum_{n=2}^{N} \alpha_n$, and decompose it into an output-oriented environment and technology index (OETI), an output-oriented technical efficiency index (OTEI), an output-oriented scale efficiency index (OSEI), and a statistical noise index (SNI). For the technical details, we refer to Njuki et al. (2018)[3] and Dakpo et al. (2021).

Global Malmquist productivity index

The global Malmquist put forward by Pastor and Lovell (2005) is calculated and decomposed as

$$TFPI_{hsit}^{GM} = \frac{D_c^G(\mathbf{x}_{it}, \mathbf{q}_{it})}{D_c^G(\mathbf{x}_{hs}, \mathbf{q}_{hs})} = \frac{D_c^t(\mathbf{x}_{it}, \mathbf{q}_{it})}{D_c^s(\mathbf{x}_{hs}, \mathbf{q}_{hs})} \times \left\{ \frac{D_c^G(\mathbf{x}_{it}, \mathbf{q}_{it})}{D_c^t(\mathbf{x}_{it}, \mathbf{q}_{it})} \times \frac{D_c^s(\mathbf{x}_{hs}, \mathbf{q}_{hs})}{D_c^G(\mathbf{x}_{hs}, \mathbf{q}_{hs})} \right\} = OTEI_{hsit} \times BPC_{hsit} \ , \quad (8)$$

where the output distance function $D^G(\mathbf{x}_{it}, \mathbf{q}_{it})$ evaluates the efficiency of unit i in year t against the global benchmark technology defined over the entire data set. OTEI is the output-oriented technical efficiency index as defined above, and BPC indicates "Best Practice Change" and is a measure of technical change. In particular, $BPC \gtreqless 1$ indicates whether the benchmark technology in period t is closer or farther away from the global benchmark technology than the benchmark technology in period s (Pastor & Lovell, 2005). The subscript c indicates that the global Malmquist index assumes constant returns to scale. Contrary to the traditional Malmquist productivity index (see Caves et al., 1982), the global Malmquist index considers only one global benchmark technology, and hence there is no need to calculate the geometric mean of two measures. As a result, the global Malmquist index satisfies the transitivity property. Another virtue of the global Malmquist index is that it is immune to infeasibility problems which often arise from the traditional Malmquist index.

REPLICATION OF O'DONNELL (2012)

This section replicates the results in O'Donnell (2012b). We briefly introduce the data and present the replicated results. We then assess the robustness of the main findings to alternative TFP indices including a parametric approach, and finally compare the results to a more recent country-level data set.

Data

O'Donnell (2012b) employs agricultural price and quantity data provided by the Economic Research Service (ERS) of the USDA. This data set has been widely used to measure US agricultural productivity (e.g., Ball et al., 2004; Ball et al., 2016; Chambers & Pieralli, 2020; Njuki et al., 2018; O'Donnell, 2014; Plastina & Lence, 2018). For each of 48 contiguous US states over the period 1960–2004, prices and implicit quantities for three outputs (crops, livestock, and other farm outputs) and four inputs (capital, labor, land, and materials) are provided. Implicit quantities are obtained by dividing revenues and costs by Fisher price indices[4] with bases equal to unity in Alabama in 1996. Importantly, the data accounts for quality changes in inputs such as chemicals, capital, or land. A detailed description of the methods are provided in Ball et al. (2016). Summary statistics for all variables used in our analysis are reported in Table S1 in the online appendix.

Results

In line with O'Donnell (2012b), we estimate separate variable-returns-to-scale production technologies for individual regions to account for different production environments, and specify moving windows (see Table S3 in the online appendix). Following the original paper, window sizes for each region are selected so that each regional frontier uses "at least as twice as many observations as there are input and output variables in the data set" (O'Donnell, 2012b, p. 883), but we test the sensitivity of this choice below. All estimations were carried out in the statistical software R (R Core Team, 2020).[5] We successfully reproduced all results presented in the original paper, including all reported decimal points (two decimals).[6] We present these results in the online appendix. For example, Figure S1 contains the replicated plots from the original paper (see Figures 2, 3, 6, and 7 in O'Donnell, 2012b), in which the profitability decomposition is shown for the example of Alabama, and TFP change is compared between Alabama, Florida, and Wyoming. The online appendix further presents profitability, TFP, and efficiency change (Table S4), output-oriented components of efficiency change (Table S5), and average annual rates of TFP and efficiency changes (Table S6) for all 48 states, corresponding to tables 2–4 in the original paper, as well averaged over all states.

To summarize the results from the original paper, we aggregated the profitability decomposition to the whole United States by taking geometric averages of yearly state-level changes relative to each states' 1960-level. For example, the average change in TFP between year 1960 and 1961 is given by $\Delta TFP_{1961,1960} = \left(\prod_{i=1}^{48} \frac{TFP_{i,1961}}{TFP_{i,1960}}\right)^{\frac{1}{48}}$, where i denotes the individual states. As shown in Figure 1, TFP gains compensated losses in terms of trade (ΔTT) (panel a), technical change (ΔTFP^*) has been the primary driver of TFP growth in US agriculture (panel b), and output-oriented technical efficiency (OTE) was higher and more stable than scale-mix efficiency (OSME) in US agriculture (panel c). The corresponding plots derived from the A-DEA index are presented in Figure S2 in the online appendix to facilitate the comparison with the European results.

Robustness

The first robustness check relates to the selection of the window size. By definition, the larger the window, the lower the technical efficiency and the larger the maximum TFP in a given period. To investigate the extent to which the window definition matters, we have estimated the technologies using small (2 years), medium (4 years), and large (8 years) windows and present the results for one state per region in Table S7. In most cases, more TFP change is attributed to technical efficiency change rather than technical change if the window size increases. Irrespective of the window size, technical change is more pronounced than technical efficiency change, which can also be seen in the average growth rates for the entire US.

Next, we assess the robustness of the original results across different TFP indices and returns to scale-assumptions. To compute the A-DEA index, we estimated shadow prices for each individual observation, assuming either varying or constant returns to scale, using the multiplier version (dual) of the Shephard input and output distance functions from a DEA representation. The

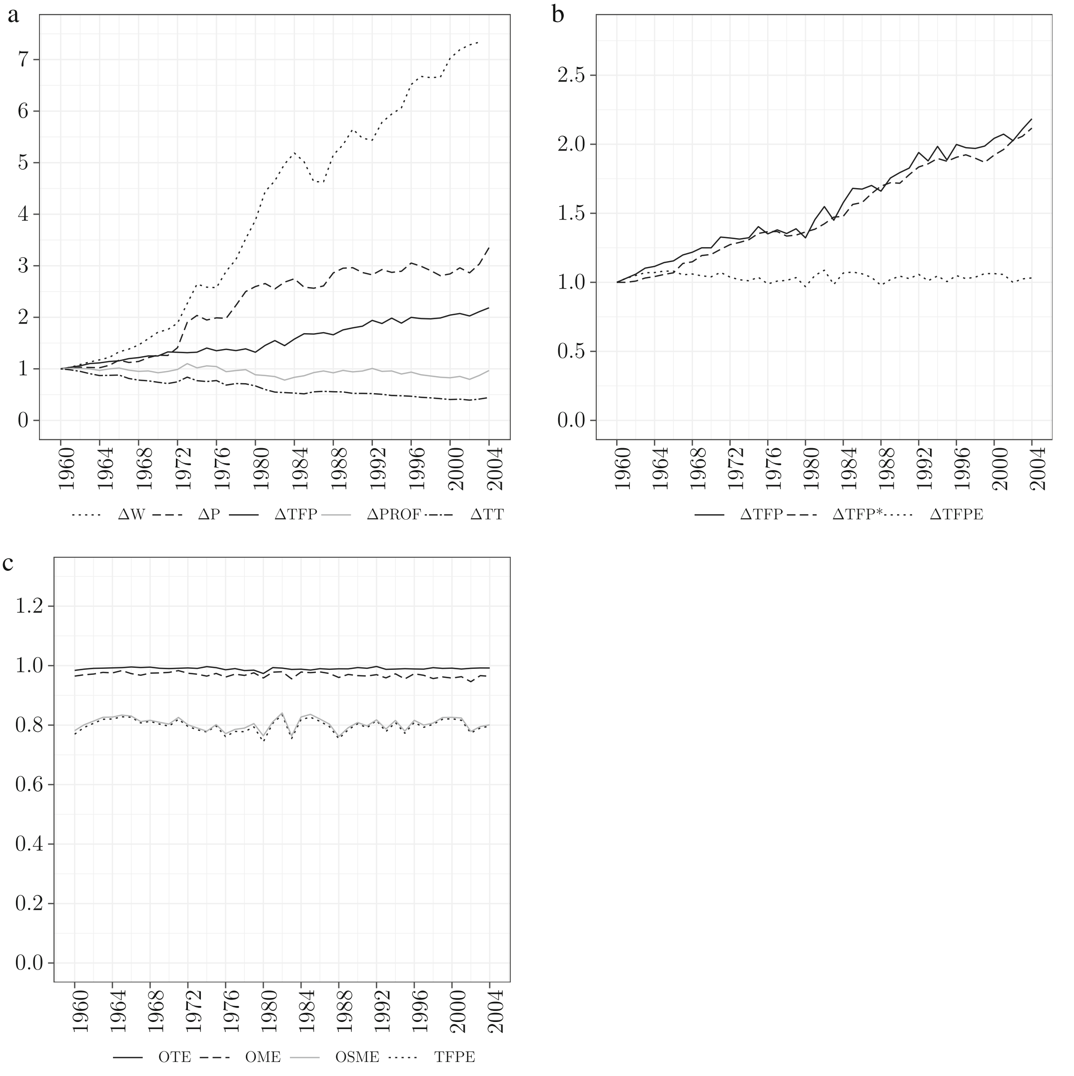

FIGURE 1 Lowe profitability decomposition for US agriculture under variable returns to scale using the state-level USDA data (1960–2004), aggregated over 48 contiguous states. (a) Profitability, quantity, and price change (1960 = 1). (b) Components of TFP change (1960 = 1). (c) Efficiency levels.

sample mean values of these estimated shadow prices are then used to calculate the aggregated output and input quantities. This procedure avoids average shadow prices (and hence, weights) with zero values. For the M-SFA index, Tables S8 and S9 in the online appendix show that the estimated coefficients for the Cobb–Douglas production frontier in Equation (6) are positive for all outputs and negative[7] for all inputs both under variable and constant returns to scale, and thus satisfy the monotonicity conditions. The global Malmquist index is only calculated under constant returns to scale, following the original paper by Pastor and Lovell (2005).

Detailed state-level results for all indices are presented in Tables S10–S21 in the appendix. The main results are summarized in Table 1, reporting the average annual growth rates (calculated as the arithmetic mean of $\ln(TFP_{2004}/\ TFP_{1960})/\ (2004-1960)$ as in the original paper)

TABLE 1 Average annual growth rates (%) in TFP and components in US agriculture (1960–2004) based on different indices.

TFP index	TFP	Technical change	Efficiency change
Lowe (VRS)	1.78	1.70	0.07
Lowe (CRS)	1.78	1.70	0.07
A-DEA (VRS)	0.83	0.91	−0.08
A-DEA (CRS)	0.73	0.74	−0.01
M-SFA (VRS)	0.89	0.90	−0.03
M-SFA (CRS)	1.02	0.99	0.01
Global Malmquist	0.64	0.63	0.00

Note: TFP is total factor productivity. VRS and CRS indicate variable returns to scale and constant returns to scale, respectively.

for TFP, technical change, and TFP efficiency change for all estimated indices. The Lowe TFP index, which does not depend on the returns to scale-assumption by construction, indicates higher TFP gains (+1.78% per year) than all other indices (e.g., +0.83% per year for the A-DEA index under variables returns to scale). However, all indices agree that technical change was the primary driver of TFP growth in US agriculture (ranging from 0.63% to 1.70% annually), while TFP efficiency change is very close to zero (between −0.08% and 0.07% annually) according to all indices. Under varying returns to scale, the (nonparametric) A-DEA and the (parametric) M-SFA indices yield similar results. Yet, under constant returns to scale, the M-SFA index results in higher TFP gains, with higher technical change than indicated by the A-DEA index. While differences between DEA- and SFA-based results may arise from the different treatments of stochastic noise (Atkinson et al., 2003), more theoretical and empirical research is needed to formally trace out the consequences of the choice between parametric and nonparametric productivity measurement on productivity and its components.

Figure 2 shows the kernel density plots (panel a) and the average TFP change across all states (panel b). A kernel-analysis procedure (Combes et al., 2012) indicates that the distributions of productivity changes are statistically significantly different[8] except for the Lowe indices under constant and variable returns to scale, which are identical by construction, and for the A-DEA and the global Malmquist index under constant returns to scale. Nevertheless, panel b shows that productivity changes from 1960 to 2004 follow a similar pattern across all indices, with highest productivity gains indicated by the Lowe indices. Overall, the comparison of the considered indices shows that the choice of the index matters for the magnitude of measured TFP growth, but the sources (i.e., technical change and efficiency change) are consistent across indices in this empirical application.

With respect to the TFP efficiency components, the Lowe indices under variable and constant returns to scale yield very similar results. In Rhode Ireland (RI), where gains in output-oriented scale efficiency (OSE) have been achieved according to the index assuming variable returns to scale (see Table S5), these gains are attributed to gains in technical efficiency (OTE) and mix efficiency (OME) when constant returns to scale are assumed. In West Virginia (WV), where the index based on variable returns to scale indicated a decrease in scale efficiency (OSE), this TFP loss is attributed to a loss in technical efficiency (OTE) under the index assuming constant returns to scale. In most states, the scale efficiency (OSE) component under

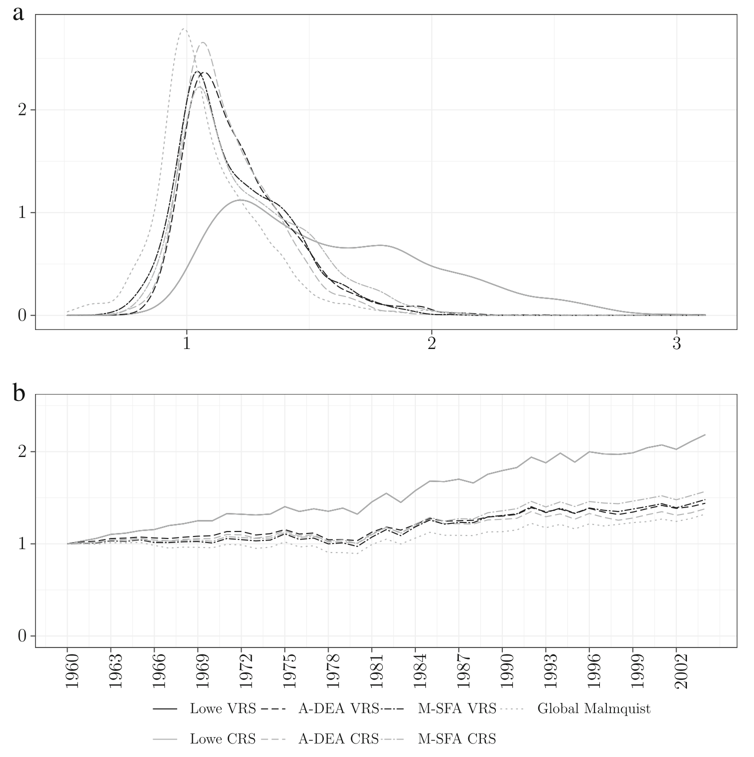

FIGURE 2 Comparison of TFP change in US agriculture with different indices and returns to scale-assumptions using the state-level USDA data (1960–2004). (a) Kernel density plots of state-level TFP changes. (b) TFP change over time at the US average. Note that the Lowe TFP index (but not its decomposition) is identical under constant and variable returns to scale by construction and hence overlapping.

variable returns to scale is already one or very close to one when assuming variable returns to scale, and hence imposing constant returns to scale has little effect on the overall results.

Replication using recent data

The publication of US state-level agricultural production data has been suspended after 2004, limiting the current policy relevance of the results. Moreover, we cannot directly compare the productivity growth rates to the rates from the EU sample, which covers the years 2000–2019 (see below). Hence, to provide a perspective on productivity change in US agriculture beyond 2004, we use US country-level data for the period 1948–2019 from the same data source, although the use of aggregate data masks differences across individual states. As described in Ball et al. (2016), the country-level variables are constructed in a very similar way as the state-level data, the main difference being that interstate transfers of intermediate inputs are considered outputs in the state-level data, and that the land variable is aggregated to the capital variable. As shown by Figure S3 in the online appendix, the Lowe TFP index suggests that US agricultural productivity growth continues after 2004 but potentially at a lower rate than in earlier decades.

EXTENSION TO EU AGRICULTURE

In this section, we extend the US evidence to EU agriculture. As mentioned above, no consistent price data exist across EU member states. While Eurostat computes price indices for each EU member state, those indices are not comparable across countries. Thus, we cannot estimate the Lowe index but instead focus on the additive TFP index constructed with estimated shadow prices (i.e., the A-DEA index), and the global Malmquist index.[9] We first provide an overview of the data and then present the results.

Data

One of the article's objectives is to compare sources of productivity change between US and EU agriculture. Ideally, we would like to employ European agricultural data (a) on the same outputs and inputs, (b) constructed with the same methods, and (c) observed over the same period as in the US data set. Unfortunately, the data collection methods vary across national statistical agencies. The primary data source for EU agricultural inputs and outputs is the Eurostat database (see below). The provided input and output categories resemble the ones in the state-level US data, and therefore allow us calculating the same productivity components including scale and mix efficiency. However, the Eurostat data set does not correct for changes in input qualities[10] and is reasonably complete only from year 2000 onwards. To facilitate a more direct comparison between US and EU agricultural productivity over an identical period, we use an additional data set that covers all countries on the globe (see below). This data set reports different input categories than the US state-level and the EU country-level data sets. Both data sets are described in the following two subsections.

Eurostat database

We obtain panel data on agricultural outputs and inputs at the country level from the Eurostat (2023) database. Specifically, we extract data on three outputs (crops, livestock, and other output) and four inputs (capital, labor, land, and materials) for 25 EU countries for the years 2000–2019.[11] All variables except for labor and land use are sourced from the "Economic Accounts for Agriculture" data set, whose main purpose is the analysis of primary income in the agricultural sector, rather than productivity measurement as in the USDA data set.[12] Other output includes both agricultural services and secondary activities (e.g., transformation of agricultural outputs) that are inseparable from agricultural activities. While the selection of input variables is in line with previous literature on productivity measurement in EU agriculture (Agri, 2016; Baležentis et al., 2021; Baráth & Fertő, 2017; Kijek et al., 2019), we distinguish more output categories than the mentioned studies in line with the output choice in the US analysis. Concerning productive inputs, labor is measured in annual working units and land is measured in hectares. The capital variable represents fixed capital consumption. Finally, intermediate inputs consist of seeds, energy consumption, fertilizer use and soil improvements, plant protection, veterinary expenses, animal feed, maintenance, services, and other goods. All outputs and inputs except labor and land are expressed in monetary terms and deflated with disaggregated output- and input-specific price indices at the national level with the base year 2005. To improve the comparability across countries, the resulting values at constant prices are converted by Eurostat to purchasing power standards using Purchasing Power Parities of each country. Table S1 in the online appendix presents descriptive statistics for the all variables next to the state-level USDA data introduced above.

USDA International Agricultural Productivity database

Our second source of agricultural production data is the IAP data set compiled by USDA-ERS. This data set provides agricultural output and input data for 172 countries over the period 1961–2020. The majority of the variables are sourced from the FAOSTAT database of the United Nations Food and Agriculture Organization (FAO), supplemented with national statistics data.[13] Output is measured as gross agricultural output at constant 2004–2006 average international prices (by contrast, the state-level US and country-level EU data use prices received by farmers). Inputs considered are land in hectares of rainfed cropland equivalents, labor (headcount without quality adjustments), capital input (machinery and livestock), fertilizer use in metric tonnes of nitrogen, phosphorus pentoxide, and potassium oxide, and animal feed in 1000 Mcal metabolizable energy. Thus, the construction of the data set differs greatly from the US state-level and the Eurostat data. For our analysis, we extract data for the US as well as 21 European countries[14], for which Table S2 in the online appendix reports descriptive statistics.

Results

In this section, we present the main results for the measurement and decomposition of TFP in European agriculture based on the A-DEA and the global Malmquist indices. We restrict our attention to the assumption of constant returns to scale as they are theoretically and empirically more consistent considering the use of country-level data. We first present the TFP change and components for the period 2000–2019, which are based on the Eurostat EAA database. Next, we directly compare TFP change between EU and the United States based on the IAP data set, covering the longer period 1961–2020.

EU productivity from 2000 to 2019

To account for different production environments, we estimate region-specific frontiers for four biogeographical regions according to the European Environment Agency (2017).[15] Temporal variations in the production environment are accounted for by estimating region-specific technologies using a moving window of observations (see Table S3 in the online appendix). As in the US case, we summarize the results on EU agriculture by computing the geometric averages of country-level productivity components. Panel a in Figure 3 shows that on average, both technical change (ΔTFP^*) (technological progress and environmental change) and TFP efficiency changes ($\Delta TFPE$) contributed to productivity growth according to the A-DEA index in EU agriculture. At the aggregate level, the yearly average TFP growth rate amounts to 0.92% ($\ln 1.19/(2019-2000)$, see numbers in Table 2) in the observed period (which is shorter and more recent compared to the period covered by the state-level data from the US). After 2014,

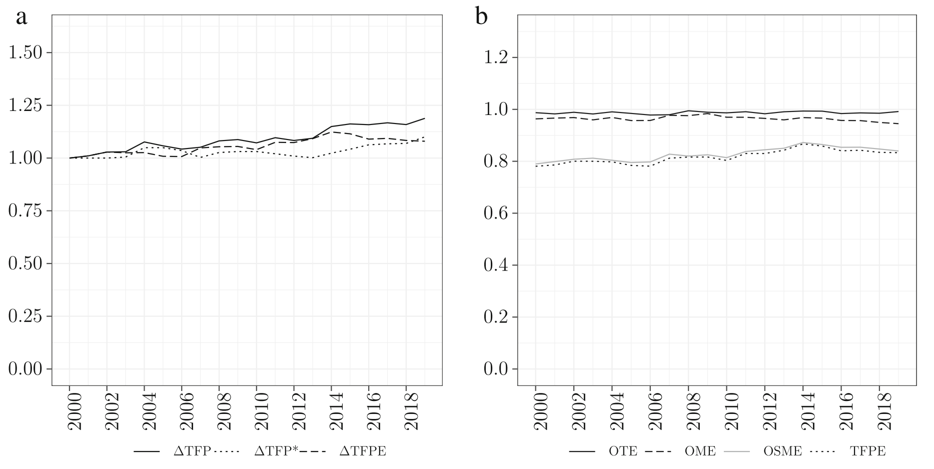

FIGURE 3 TFP decomposition for EU agriculture under constant returns to scale using the A-DEA index and the Eurostat data (2000–2019), aggregated over 25 countries. (a) Components of TFP change. (b) Efficiency levels.

there is a slight decrease in efficiency, while more gains arise from the technical component. Panel b in Figure 3 reveals that output-oriented technical efficiency (OTE) and mix efficiency (OME) were high and fairly stable over the data period, while improvements have been achieved in scale-mix efficiency (OSME). As there is no scale effect under the assumption of constant returns to scale, the changes in OSME are entirely due to residual mix efficiency.[16] This is potentially in line with the structural change, especially sectoral re-specialization, experienced by the European agriculture (Neuenfeldt et al., 2019).

Table 2 shows that at the individual country level, Latvia achieved the largest TFP gains (+74%) among all EU countries over the sample period, followed by Belgium (+73%), Romania (+58%), and Poland (+47%) according to the A-DEA index. As in the case of the Lowe index, the transitivity property also allows consistent comparisons across units. For example, in 2019, the Netherlands were 16% more productive than Germany ($\Delta TFP = 0.57/0.49 = 1.16$), and Belgium and Spain are the most productive countries in 2019. Technical change varies between −13% (i.e., technical regress) in the Mediterranean region and +21% (i.e., technical progress) in the Atlantic region. Most countries achieved gains in TFP efficiency (e.g., +62% in Latvia), while some countries also experienced losses (e.g., −17% in France). Belgium, Denmark, Estonia and Sweden were fully TFP efficient in 2019, and the largest gains in TFP efficiency over the data period were achieved by Latvia, Spain, and Belgium. Zooming in on the sources of TFP efficiency change, Table 3 shows that gains in TFP efficiency were mainly driven by gains in output-oriented scale-mix efficiency (OSME), as seen above in the discussion of the aggregate results.

The global Malmquist TFP index, presented in Table 4, indicates lower TFP gains in EU agriculture than the A-DEA index, at a yearly average growth rate of 0.55% ($\ln 1.11/(2019-2000)$) during the observed period. According to this index, largest TFP gains were achieved by Slovakia (+64%), Hungary (+50%), Belgium (+34%), and Finland (+27%). The most productive countries in 2019 are Belgium, Denmark, Spain, Greece, and Ireland. Except for Greece, these countries are also among the top five TFP countries according to the A-DEA index. Similar to the A-DEA index, the global Malmquist index attributes the main TFP growth to improvements in the best practice gap and the technology gap ratio, which are

TABLE 2 TFP, technical change, and efficiency change in EU agriculture (2000–2019) using the A-DEA index under CRS.

	TFP			TFP* (=OET)			TFPE		
Country	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**
AUT	0.38	0.46	1.20	0.50	0.60	1.19	0.76	0.76	1.00
BEL	0.40	0.69	1.73	0.57	0.69	1.21	0.70	1.00	1.43
CZE	0.43	0.47	1.10	0.50	0.60	1.19	0.85	0.79	0.92
DEU	0.50	0.49	0.98	0.50	0.60	1.19	0.99	0.81	0.82
DNK	0.46	0.60	1.29	0.50	0.60	1.19	0.92	1.00	1.08
ESP	0.52	0.66	1.27	0.78	0.68	0.87	0.68	0.98	1.45
EST	0.32	0.42	1.32	0.39	0.42	1.07	0.82	1.00	1.23
FIN	0.29	0.34	1.17	0.39	0.42	1.07	0.73	0.80	1.09
FRA	0.51	0.51	1.00	0.57	0.69	1.21	0.89	0.74	0.83
GBR	0.53	0.54	1.03	0.57	0.69	1.21	0.93	0.79	0.85
GRC	0.50	0.52	1.04	0.78	0.68	0.87	0.64	0.77	1.20
HUN	0.35	0.49	1.41	0.50	0.60	1.19	0.69	0.82	1.19
IRL	0.49	0.57	1.17	0.57	0.69	1.21	0.87	0.84	0.97
ITA	0.51	0.51	1.00	0.78	0.68	0.87	0.66	0.75	1.15
LTU	0.31	0.36	1.15	0.39	0.42	1.07	0.79	0.84	1.07
LUX	0.50	0.46	0.91	0.50	0.60	1.19	0.99	0.76	0.77
LVA	0.21	0.37	1.74	0.39	0.42	1.07	0.54	0.87	1.62
MLT	0.76	0.65	0.86	0.78	0.68	0.87	0.97	0.96	0.98
NLD	0.57	0.57	1.00	0.57	0.69	1.21	1.00	0.83	0.83
POL	0.35	0.51	1.47	0.50	0.60	1.19	0.69	0.85	1.23
PRT	0.44	0.50	1.13	0.78	0.68	0.87	0.57	0.73	1.29
ROU	0.27	0.42	1.58	0.50	0.60	1.19	0.53	0.70	1.32
SVK	0.31	0.41	1.31	0.50	0.60	1.19	0.62	0.68	1.10
SVN	0.37	0.46	1.25	0.50	0.60	1.19	0.73	0.76	1.05
SWE	0.38	0.42	1.10	0.39	0.42	1.07	0.98	1.00	1.02
EU25			1.19			1.10			1.08

Note: TFP is total factor productivity, TFP* is the maximum possible TFP based on the output-oriented environment and technology (OET) index, and TFPE is TFP efficiency.

measures of technical change, while output-oriented technical efficiency is high and stable throughout the data period.

EU versus US productivity from 1961 to 2020

Finally, we turn to the results for the period 1961–2020 based on the IAP data set. With this data, we estimate the technology jointly for all available 24 EU countries or regions and the

TABLE 3 Output-oriented components of efficiency change in EU agriculture (2000–2019) using the A-DEA index under CRS.

	TFPE = OTE × OSME			OTE			OSE			OME			OSME		
Country	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**
AUT	0.76	0.76	1.00	1.00	0.98	0.98	1.00	1.00	1.00	0.95	0.99	1.05	0.76	0.78	1.02
BEL	0.70	1.00	1.43	1.00	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.05	0.70	1.00	1.43
CZE	0.85	0.79	0.92	0.96	1.00	1.04	1.00	1.00	1.00	1.00	0.86	0.86	0.88	0.79	0.89
DEU	0.99	0.81	0.82	1.00	0.99	0.99	1.00	1.00	1.00	1.00	0.92	0.92	0.99	0.82	0.83
DNK	0.92	1.00	1.08	0.99	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	0.93	1.00	1.07
ESP	0.68	0.98	1.45	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.02	0.68	0.98	1.45
EST	0.82	1.00	1.23	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.82	1.00	1.23
FIN	0.73	0.80	1.09	0.98	1.00	1.02	1.00	1.00	1.00	0.94	0.92	0.98	0.74	0.80	1.08
FRA	0.89	0.74	0.83	1.00	0.99	0.99	1.00	1.00	1.00	0.96	0.89	0.93	0.89	0.74	0.84
GBR	0.93	0.79	0.85	0.98	1.00	1.02	1.00	1.00	1.00	1.00	0.96	0.96	0.94	0.79	0.84
GRC	0.64	0.77	1.20	1.00	1.00	1.00	1.00	1.00	1.00	0.91	0.83	0.91	0.64	0.77	1.20
HUN	0.69	0.82	1.19	1.00	1.00	1.00	1.00	1	1.00	0.91	0.91	1.00	0.69	0.82	1.19
IRL	0.87	0.84	0.97	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.01	0.87	0.84	0.97
ITA	0.66	0.75	1.15	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.94	0.66	0.75	1.15
LTU	0.79	0.84	1.07	1.00	1.00	1.00	1.00	1.00	1.00	0.89	0.96	1.09	0.79	0.84	1.07
LUX	0.99	0.76	0.77	1.00	0.98	0.98	1.00	1.00	1.00	1.00	0.87	0.87	0.99	0.77	0.78
LVA	0.54	0.87	1.62	0.92	1.00	1.08	1.00	1.00	1.00	0.99	1.00	1.01	0.58	0.87	1.50
MLT	0.97	0.96	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.97	0.97	0.96	0.98
NLD	1.00	0.83	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.83	0.83
POL	0.69	0.85	1.23	0.96	1.00	1.04	1.00	1	1.00	0.99	0.99	1.00	0.72	0.85	1.18
PRT	0.57	0.73	1.29	0.90	0.89	0.98	1.00	1	1.00	0.97	0.92	0.95	0.63	0.82	1.31

TABLE 3 (Continued)

	TFPE = OTE × OSME			OTE			OSE			OME			OSME		
Country	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**
ROU	0.53	0.70	1.32	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.83	0.85	0.53	0.70	1.32
SVK	0.62	0.68	1.10	1.00	0.98	0.98	1.00	1.00	1.00	0.73	0.90	1.23	0.62	0.69	1.12
SVN	0.73	0.76	1.05	0.98	0.97	0.99	1.00	1	1.00	0.96	0.96	1.00	0.74	0.79	1.06
SWE	0.98	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.02
EU25			1.08			1.00			1.00			0.98			1.07

Note: TFPE is TFP efficiency, OTE is output-oriented technical efficiency, OSE is output-oriented scale efficiency, OME is output-oriented mix efficiency, and OSME is output-oriented scale-mix efficiency. OSE is one by construction under constant returns to scale.

TABLE 4 TFP decomposition for EU agriculture (2000–2019) using the Global Malmquist index.

	TFP			OTE			BPG			TGR		
Country	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**	**2000**	**2019**	**Δ**
AUT	0.74	0.85	1.15	1.00	0.98	0.98	1.00	1.00	1.00	0.74	0.87	1.17
BEL	0.75	1.00	1.34	1.00	1.00	1.00	0.78	1.00	1.27	0.95	1.00	1.05
CZE	0.65	0.81	1.23	0.96	1.00	1.04	0.87	0.93	1.07	0.78	0.87	1.11
DEU	0.81	0.83	1.02	1.00	0.99	0.99	0.91	0.98	1.08	0.90	0.86	0.96
DNK	0.80	1.00	1.25	0.99	1.00	1.01	0.85	1.00	1.18	0.96	1.00	1.05
ESP	0.91	1.00	1.09	1.00	1.00	1.00	0.92	1.00	1.09	1.00	1.00	1.00
EST	0.80	0.73	0.91	1.00	1.00	1.00	1.00	1.00	1.00	0.80	0.73	0.91
FIN	0.50	0.63	1.27	0.98	1.00	1.02	0.95	1.00	1.05	0.53	0.63	1.19
FRA	0.82	0.93	1.15	1.00	0.99	0.99	0.99	0.99	1.01	0.83	0.95	1.15
GBR	0.95	0.97	1.02	0.98	1.00	1.02	0.99	1.00	1.01	0.97	0.97	1.00
GRC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HUN	0.56	0.84	1.50	1.00	1.00	1.00	1.00	1.00	1.00	0.56	0.84	1.50
IRL	0.91	1.00	1.10	1.00	1.00	1.00	0.97	1.00	1.03	0.94	1.00	1.06
ITA	0.99	0.95	0.96	1.00	1.00	1.00	0.99	0.95	0.96	1.00	1.00	1.00
LTU	0.62	0.58	0.94	1.00	1.00	1.00	0.88	1.00	1.14	0.71	0.58	0.82
LUX	0.87	0.81	0.93	1.00	0.98	0.98	0.99	1.00	1.01	0.88	0.83	0.94
LVA	0.61	0.73	1.18	0.92	1.00	1.08	0.99	1.00	1.01	0.67	0.73	1.08
MLT	1.00	0.97	0.97	1.00	1.00	1.00	1.00	0.97	0.97	1.00	1.00	1.00
NLD	0.98	0.99	1.01	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.01
POL	0.67	0.77	1.14	0.96	1.00	1.04	0.89	1.00	1.12	0.79	0.77	0.97
PRT	0.81	0.78	0.96	0.90	0.89	0.98	0.89	0.89	0.99	1.00	0.99	0.99
ROU	0.95	0.88	0.93	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.88	0.93
SVK	0.52	0.85	1.64	1.00	0.98	0.98	1.00	1.00	1.00	0.52	0.87	1.67
SVN	0.75	0.89	1.19	0.98	0.97	0.99	0.92	1.00	1.08	0.83	0.92	1.11
SWE	0.66	0.72	1.09	1.00	1.00	1.00	1.00	1.00	1.00	0.66	0.72	1.09
EU25			1.11			1.00			1.04			1.06

Note: TFP is total factor productivity, OTE is output-oriented technical efficiency, BPG is the best practice gap, and TGR is a technology gap ratio capturing technical and environmental differences across the four biogeographical regions.

United States. Having only one observation for the entire United States, we cannot separate distinct production environments there (as done with the 10 distinct regions in the state-level analysis), and hence do not decompose productivity change into its components.[17] Panel a in Figure 4 shows the productivity change for selected European countries as well as for the United States based on the A-DEA index. As seen in Panel b, average TFP growth in EU and US agriculture has been similar until about 2005, after which the EU experienced a slightly negative TFP change, which was not found for in the country-level EU data from Eurostat. At the individual country-level, some EU countries or regions (Benelux, Cyprus, Germany, Denmark, Spain, Netherlands, and Portugal) achieved higher TFP gains than the US average according to the A-DEA index (see Table 5). At the

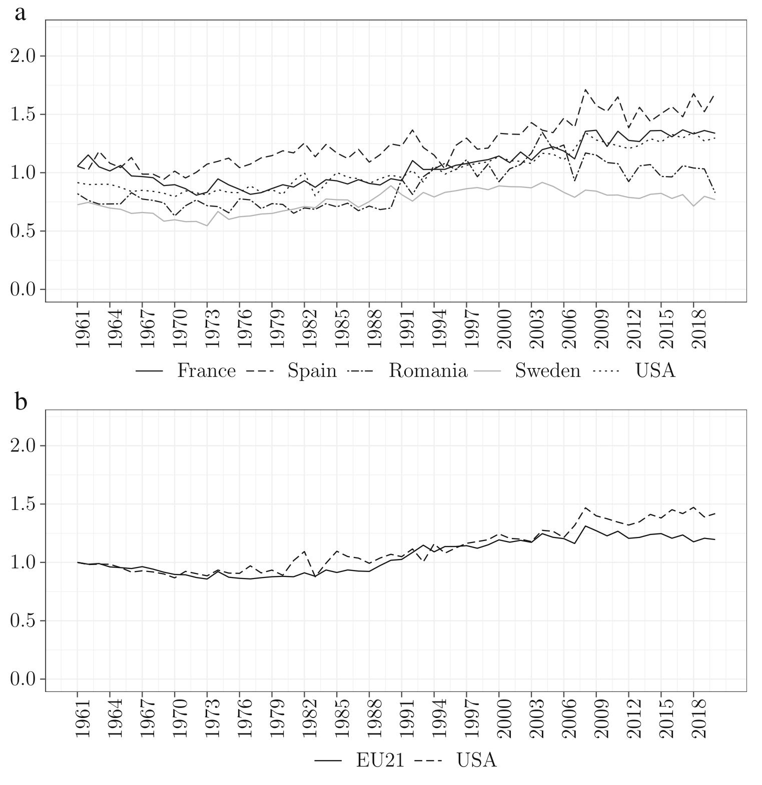

FIGURE 4 Agricultural TFP changes (1961–2020) in selected EU countries and the United States (a) and in aggregate EU and the United States (b), based on the A-DEA TFP index under constant returns to scale and the International Agricultural Productivity data.

aggregate level, the US achieved higher gains in TFP over the years 1961–2016 than the EU (+42% vs. +20%). This difference is much more pronounced when considering the global Malmquist index, as shown in the same table (+60% vs. +8%), according to which none of the European countries has achieved TFP gains as high as the aggregate US. In absolute terms, few European countries are slightly more productive than or as productive as the aggregate United States in 2020, according to the global Malmquist index, for example the Benelux countries, Spain, or Ireland, which were also among the most productive countries according to the Eurostat data.

DISCUSSION AND CONCLUSION

In this article, we replicated the measurement and decomposition of state-level TFP in US agriculture (1960–2004) in O'Donnell (2012b), assessed its robustness to alternative indices, and provided new estimates for TFP and its components in EU agriculture. We successfully reproduced all results from the original paper and found consistent evidence that technical change (encompassing technological progress and environmental change) was the main driver of TFP growth in US agriculture from 1960 to 2004. We showed that this result was not driven by the choice of window sizes and that the same conclusion can be derived from a nonparametric additive TFP index that uses estimated shadow prices instead of observed prices as aggregation

TABLE 5 TFP in EU and US agriculture using the A-DEA index and the global Malmquist index and the International Agricultural Productivity data (1961–2020).

	A-DEA TFP			Global Malmquist TFP		
Region	**1961**	**2020**	**Δ**	**1961**	**2020**	**Δ**
AUT	0.29	0.32	1.09	0.76	0.90	1.19
BGR	0.27	0.22	0.81	0.71	0.84	1.19
BLX	0.32	0.58	1.83	0.91	1.00	1.09
CSK	0.30	0.30	0.99	0.63	0.77	1.22
CYP	0.27	0.38	1.44	0.69	0.77	1.11
DEU	0.24	0.41	1.72	0.59	0.79	1.33
DNK	0.25	0.38	1.52	0.57	0.84	1.46
ESP	0.31	0.49	1.59	0.73	1.00	1.37
EST	0.38	0.23	0.60	1.00	0.94	0.94
FIN	0.21	0.23	1.13	0.60	0.60	1.00
FRA	0.31	0.39	1.27	0.82	0.93	1.13
GBR	0.26	0.36	1.37	0.61	0.79	1.29
GRC	0.45	0.58	1.28	1.00	1.00	1.00
HUN	0.26	0.31	1.18	0.58	0.76	1.31
IRL	0.29	0.34	1.18	0.92	1.00	1.08
ITA	0.42	0.46	1.11	0.99	0.93	0.94
LTU	0.25	0.29	1.15	1.00	1.00	1.00
LVA	0.23	0.25	1.10	0.98	0.79	0.80
MLT	0.48	0.43	0.91	1.00	0.82	0.82
NLD	0.33	0.54	1.64	0.74	1.00	1.35
POL	0.37	0.41	1.10	0.83	1.00	1.20
PRT	0.33	0.49	1.49	0.97	0.79	0.82
ROU	0.24	0.24	1.01	0.80	0.48	0.61
SWE	0.21	0.23	1.06	0.55	0.72	1.31
USA	0.27	0.38	1.42	0.61	0.98	1.60
EU aggregated			1.20			1.08

Note: TFP is total factor productivity.

weights (A-DEA index), from a parametric multiplicative TFP index based on an econometrically estimated output distance function (M-SFA index), and from a global Malmquist index. However, the Lowe TFP index presented in the original study indicates higher annual average TFP growth rates than the remaining indices considered in our replication study.

Extending the analysis to EU agriculture (2000–2019) and considering the A-DEA index, which is equivalent to the Lowe TFP index except for the use of estimated shadow prices rather than observed prices for the outputs and inputs weights, we find that both technical change and TFP efficiency changes contributed to changes in country-level TFP during the years 2000 to 2019. As in the US case, output-oriented technical efficiency is high and stable, a result which is also supported by the global Malmquist index. Furthermore, we find a strong overlap in the list of the most productive countries identified by the A-DEA and global Malmquist indices.

The comparability of the described results on TFP development in EU and US agriculture, based on the country-level data from Eurostat and the state-level data from USDA, is limited due to different data periods covered in the respective data sets as well as due to different methodologies for the measurement of input and output quantities. To overcome this limitation, we employed a third data set—the International Agricultural Productivity data set—which provides the globally most complete and consistent information on agricultural output and input use. This analysis confirms that productivity growth was higher in the United States than in the EU on average, both under the A-DEA index and the global Malmquist index. However, the difference was much more pronounced under the latter, and the analysis based on the International Agricultural Productivity data revealed a slight decrease in TFP in European agriculture after 2006, which is not found in our analysis of the Eurostat data.

Our study has several implications for policy. First, the findings suggest that investing in R&D may lead to higher payoffs for productivity than investing in training programs, at least when evaluated at the aggregate level, as output-oriented technical efficiency is at very high levels both at the US state-level and at the EU country-level. Accordingly, the EU farm to fork strategy assigns an important role to research, innovation, and technology, especially in the direction of sustainable agriculture (Sonnino et al., 2020). Furthermore, improvements in the output-oriented scale-mix component contributed to productivity growth in EU agriculture according to the employed A-DEA index. This result may be in line with ongoing structural change characterized at the sectoral level, such as the declining number of farms or production re-specialization (e.g., Baráth & Fertő, 2017; Neuenfeldt et al., 2019). Second, differences in environmental and health regulations may be a possible explanation for more pronounced technical TFP growth through technical progress in the United States compared to the EU. In the past decades, the EU has implemented increasingly strict regulations relating to pesticide (Möhring et al., 2020) and nitrogen (Zhang et al., 2015) use. Furthermore, the use of antibiotics as growth promoters in animal production (McBride et al., 2008) has been forbidden in the EU in 2006, and genetically modified organisms are more strictly regulated in the EU (Qaim, 2020; Smart et al., 2017) than in the United States (Kaye-Blake et al., 2008). These policies, besides potential environmental changes such as weather conditions, may slow down technical progress, although the identification of causal effects of such policy or environmental changes on technical change is beyond the scope of this replication study. Third, our results also indicate that productivity change and its components differ widely across states in the United States and across countries in the EU. The heterogeneity in production conditions implies that policy instruments aiming at increasing productivity should be tailored to the specific needs of individual countries or states. The common agricultural policy (CAP) recognizes this by setting common targets, while individual countries have flexibility in the implementation of certain policies. In this context, heterogeneity in the sources of productivity change provides opportunities for researchers and policymakers to learn from developments in other countries or states.

Overall, this replication study highlights the importance of consistent and high quality data on agricultural production for the measurement and decomposition of TFP. Contrary to the United States state-level data, the European data on agricultural output and input use published by Eurostat does not consider quality changes in inputs, which we regard as an important avenue for further research. Further important extensions to our work include a comparison of the contribution of weather variations to TFP changes (see, e.g., Njuki et al., 2018; Chambers et al., 2020; O'Donnell, 2022) and the consideration of environmental outcomes in the measurement of TFP (see, e.g., Baležentis et al., 2021; Bureau & Antón, 2022). Finally, the causal identification of the role of sectoral policies and structural change in explaining country- and state-level TFP deserves further attention in future research.

ACKNOWLEDGEMENT

Open access funding provided by Eidgenossische Technische Hochschule Zurich.

ORCID

Stefan Wimmer https://orcid.org/0000-0002-2628-748X

ENDNOTES

[1] As argued by other authors, using fixed weights may allow "incoherent" comparisons of different possible past time periods (e.g., Färe & Zelenyuk, 2021). One transitive TFP index that does not use fixed weights is the benefit-of-the-doubt index.

[2] Under specific choices and additional assumptions on the technology, the Färe-Primont TFP index developed in O'Donnell (2014) simplifies to this index (see Briec et al., 2018, for details]briec_testing_2018-1.

[3] The approach by Njuki et al. (2018) differs in that it includes environmental variables and hence separates technological progress and environmental change. By contrast, our measure of technical change encompasses both technological progress and environmental change as explained above.

[4] Although the EKS procedure was applied to make the price indices transitive, they do not satisfy the unity property (O'Donnell, 2012b).

[5] The computations largely rely on the *productivity* package (Dakpo et al., 2018). Codes are available in supplementary material online and on Github (https://github.com/swimmer008/Ag-Productivity-US-EU).

[6] The variables were used exactly as prepared and published by USDA. As the data undergo quality checks prior to publication, neither we nor the original author undertook further data cleaning steps.

[7] The input weights are constructed using the reversed signs of the input coefficients.

[8] For each pair of distributions, we tested the null hypothesis that there is no shift and dilation between the two.

[9] For the EU case, we only estimated nonparametric indices. Estimating the distance function using stochastic frontier analysis resulted in negative elasticity estimates, which is inconsistent with economic theory. We also employed a Bayesian regression technique to impose monotonicity, but did not achieve convergence for the posteriors. A possible reason may be the much smaller sample size compared to the state-level US data.

[10] As discussed in Ball et al. (2016), there is a debate whether quality improvements should be regarded as input growth or productivity growth, although economic theory guides to the former. Given the data availability, we are not able to control for such quality changes in EU agriculture, and this limitation must be kept in mind when interpreting the results.

[11] The countries include all EU-27 member states except Bulgaria (missing data in 2000, 2001, and 2005) and Cyprus (missing data in 2000–2002). For Italy in 2009, France in 2006 and 2009, the utilized agricultural area is imputed as the average of prior and posterior years.

[12] Output data and input data on capital and materials come from Eurostat data table *aact_eaa03*, and land and labor variables come from Eurostat data tables *apro_cpsh1* and *aact_ali01*, respectively.

[13] The data sources and methodologies are described in detail in Fuglie (2012, 2015).

[14] Some countries are summarized to groups depending to ensure long-term data availability.

[15] We merged mountain and continental regions because the separation at the country level was not clear-cut. Additionally, we re-estimated the technologies for the five regions identified in Baráth and Fertő (2017) using cluster analysis based on output shares and weather variables, which yielded very similar results.

[16] O'Donnell (2012a) describes that points on the unrestricted frontier may have different output and input mixes, although all of them are mix-efficient. As a result, OSME encompasses both scale and residual mix effects.

[17] The necessary assumption would be that both the European countries and the US have access to the same technology. Productivity differences arising from different production environments or policy restrictions would therefore be captured in the TFP efficiency term rather than in the technical component, and hence the results on the TFP components would not be comparable to our main analysis. The overall TFP measure, however, is not affected by this assumption.

REFERENCES

Agri, D. 2016. Productivity in EU Agriculture—Slowly but Steadily Growing. No. 10 in EU Agricultural Market Briefs, Brussels.

Aigner, D., C. A. K. Lovell, and P. Schmidt. 1977. "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6(1): 21–37.

Andersen, M. A., J. M. Alston, and P. G. Pardey. 2012. "Capital Use Intensity and Productivity Biases." *Journal of Productivity Analysis* 37(1): 59–71.

Atkinson, S. E., C. Cornwell, and O. Honerkamp. 2003. "Measuring and Decomposing Productivity Change." *Journal of Business & Economic Statistics* 21(2): 284–94.

Baležentis, T., S. Blancard, Z. Shen, and D. Štreimikienė. 2021. "Analysis of Environmental Total Factor Productivity Evolution in European Agricultural Sector." *Decision Sciences* 52(2): 483–511.

Balk, B. M. 2001. "Scale Efficiency and Productivity Change." *Journal of Productivity Analysis* 15(3): 159–83.

Ball, E. V., S. L. Wang, R. Nehring, and R. Mosheim. 2016. "Productivity and Economic Growth in U.S. Agriculture: A New Look." *Applied Economic Perspectives and Policy* 38(1): 30–49.

Ball, V. E., C. Hallahan, and R. Nehring. 2004. "Convergence of Productivity: An Analysis of the Catch-up Hypothesis within a Panel of States." *American Journal of Agricultural Economics* 86(5): 1315–21.

Baráth, L., and I. Fertő. 2017. "Productivity and Convergence in European Agriculture." *Journal of Agricultural Economics* 68(1): 228–48.

Briec, W., K. Kerstens, D. Prior, and I. Van de Woestyne. 2018. "Testing General and Special Färe-Primont Indices: A Proposal for Public and Private Sector Synthetic Indices of European Regional Expenditures and Tourism." *European Journal of Operational Research* 271(2): 756–68.

Brümmer, B., T. Glauben, and G. Thijssen. 2002. "Decomposition of Productivity Growth Using Distance Functions: The Case of Dairy Farms in Three European Countries." *American Journal of Agricultural Economics* 84(3): 628–44.

Bureau, J. C., and J. Antón. 2022. "Agricultural Total Factor Productivity and the Environment: A Guide to Emerging Best Practices in Measurement." In *OECD Food, Agriculture and Fisheries Papers No. 177*. Paris: OECD Publishing.

Capalbo, S. M. 1988. "Measuring the Components of Aggregate Productivity Growth in U.S. Agriculture." *Western Journal of Agricultural Economics* 13(1): 53–62.

Caves, D. W., L. R. Christensen, and W. E. Diewert. 1982. "The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity." *Econometrica* 50(6): 1393–414.

Chambers, R. G., and S. Pieralli. 2020. "The Sources of Measured US Agricultural Productivity Growth: Weather, Technological Change, and Adaptation." *American Journal of Agricultural Economics* 102(4): 1198–226.

Chambers, R. G., S. Pieralli, and Y. Sheng. 2020. "The Millennium Droughts and Australian Agricultural Productivity Performance: A Nonparametric Analysis." *American Journal of Agricultural Economics* 102(5): 1383–403.

Coelli, T. J., and D. S. P. Rao. 2005. "Total Factor Productivity Growth in Agriculture: A Malmquist Index Analysis of 93 Countries, 1980–2000." *Agricultural Economics* 32(s1): 115–34.

Combes, P. P., G. Duranton, L. Gobillon, D. Puga, and S. Roux. 2012. "The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection." *Econometrica* 80(6): 2543–94.

Cuesta, R. A. 2000. "A Production Model with Firm-Specific Temporal Variation in Technical Inefficiency: With Application to Spanish Dairy Farms." *Journal of Productivity Analysis* 13(2): 139–58.

Dakpo, K. H., Y. Desjeux, and L. Latruffe. 2018. Productivity: Indices of Productivity Using Data Envelopment Analysis (DEA)." R Package Version 1.1.0.

Dakpo, K. H., L. Latruffe, Y. Desjeux, and P. Jeanneaux. 2021. "Latent Class Modelling for a Robust Assessment of Productivity: Application to French Grazing Livestock Farms." *Journal of Agricultural Economics* 72(3): 760–81.

European Environment Agency. 2017. *Climate Change, Impacts and Vulnerability in Europe 2016: An Indicator Based Report. No. 1/2017 in EEA Report*. Luxembourg: Publications Office of the European Union.

Eurostat. 2023. *Eurostat Database*. Brussels: European Statistical Office (Eurostat). https://ec.europa.eu/eurostat/data/database.

FAO. 2017. *The Future of Food and Agriculture: Trends and Challenges*. Rome: Food and Agriculture Organization of the United Nations (FAO).

FAO. 2020. *FAOSTAT: Value of Agricultural Production*. Rome: Food and Agriculture Organization of the United Nations (FAO). https://www.fao.org/faostat/en/#data/QV.

Färe, R., and S. Grosskopf. 1990. "A Distance Function Approach to Price Efficiency." *Journal of Public Economics* 43(1): 123–6.

Färe, R., and V. Zelenyuk. 2021. "On Aggregation of Multi-Factor Productivity Indexes." *Journal of Productivity Analysis* 55(2): 107–33.

Farrell, M. J. 1957. "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society. Series A (General)* 120(3): 253–90.

Fuglie, K. 2015. "Accounting for Growth in Global Agriculture." *Bio-based and Applied Economics* 4(3): 201–34.

Fuglie, K. O. 2012. "Productivity Growth and Technology Capital in the Global Agricultural Economy." In *Productivity Growth in Agriculture: An International Perspective*, edited by K. O. Fuglie, S. L. Wang, and V. E. Ball, 335–68. Wallingford: CABI.

Fuglie, K. O. 2018. "Is Agricultural Productivity Slowing?" *Global Food Security* 17: 73–83.

Grosskopf, S., D. Margaritis, and V. Valdmanis. 1995. "Estimating Output Substitutability of Hospital Services: A Distance Function Approach." *European Journal of Operational Research* 80(3): 575–87.

Jorgenson, D. W., and Z. Griliches. 1967. "The Explanation of Productivity Change." *The Review of Economic Studies* 34(3): 249–83.

Kaye-Blake, W. H., C. M. Saunders, and S. Cagatay. 2008. "Genetic Modification Technology and Producer Returns: The Impacts of Productivity, Preferences, and Technology Uptake." *Applied Economic Perspectives and Policy* 30(4): 692–710.

Kijek, A., T. Kijek, A. Nowak, and A. Skrzypek. 2019. "Productivity and its Convergence in Agriculture in New and Old European Union Member States." *Agricultural Economics—Czech* 65(1): 1–9.

Lowe, J. 1823. *The Present State of England in Regard to Agriculture, Trade and Finance: With a Comparison of the Prospects of England and France*, 2nd ed. London: Longman, Hurst, Rees, Orme, and Brown.

McBride, W. D., N. Key, and K. H. Mathews, Jr. 2008. "Subtherapeutic Antibiotics and Productivity in U.S. Hog Production." *Applied Economic Perspectives and Policy* 30(2): 270–88.

Meeusen, W., and J. van Den Broeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review* 18(2): 435–44.

Möhring, N., K. Ingold, P. Kudsk, F. Martin-Laurent, U. Niggli, M. Siegrist, B. Studer, A. Walter, and R. Finger. 2020. "Pathways for Advancing Pesticide Policies." *Nature Food* 1(9): 535–40.

Mugera, A. W., M. R. Langemeier, and A. Ojede. 2016. "Contributions of Productivity and Relative Price Changes to Farm-Level Profitability Change." *American Journal of Agricultural Economics* 98(4): 1210–29.

Neuenfeldt, S., A. Gocht, T. Heckelei, and P. Ciaian. 2019. "Explaining Farm Structural Change in the European Agriculture: A Novel Analytical Framework." *European Review of Agricultural Economics* 46(5): 713–68.

Njuki, E., B. E. Bravo-Ureta, and C. J. O'Donnell. 2018. "A New Look at the Decomposition of Agricultural Productivity Growth Incorporating Weather Effects." *PLoS One* 13(2): e0192432.

O'Donnell, C. J. 2011. "The Sources of Productivity Change in the Manufacturing Sectors of the U.S. Economy." CEPA Working Papers Series WP072011, School of Economics, University of Queensland, Australia.

O'Donnell, C. J. 2012a. "An Aggregate Quantity Framework for Measuring and Decomposing Productivity Change." *Journal of Productivity Analysis* 38(3): 255–72.

O'Donnell, C. J. 2012b. "Nonparametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture." *American Journal of Agricultural Economics* 94(4): 873–90.

O'Donnell, C. J. 2014. "Econometric Estimation of Distance Functions and Associated Measures of Productivity and Efficiency Change." *Journal of Productivity Analysis* 41(2): 187–200.
O'Donnell, C. J. 2016. "Using Information about Technologies, Markets and Firm Behaviour to Decompose a Proper Productivity Index." *Journal of Econometrics* 190(2): 328–40.
O'Donnell, C. J. 2022. "Estimating the Effects of Weather and Climate Change on Agricultural Productivity." *Q Open* 2(2): qoac018.
Pastor, J. T., and C. A. K. Lovell. 2005. "A Global Malmquist Productivity Index." *Economics Letters* 88: 266–71.
Plastina, A., and S. H. Lence. 2018. "A Parametric Estimation of Total Factor Productivity and its Components in U.S. Agriculture." *American Journal of Agricultural Economics* 100: 1091–119.
Qaim, M. 2020. "Role of New Plant Breeding Technologies for Food Security and Sustainable Agricultural Development." *Applied Economic Perspectives and Policy* 42: 129–50.
R Core Team. 2020. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.
Shephard, R. W. 1953. *Cost and Production Functions*. Princeton: Princeton University Press.
Sipiläinen, T. 2007. "Sources of Productivity Growth on Finnish Dairy Farms—Application of an Input Distance Function." *Acta Agriculturae Scandinavica, Section C—Food Economics* 4: 65–76.
Smart, R. D., M. Blum, and J. Wesseler. 2017. "Trends in Approval Times for Genetically Engineered Crops in the United States and the European Union." *Journal of Agricultural Economics* 68: 182–98.
Sonnino, R., C. Callenius, L. Lähteenmäki, J. Breda, J. Cahill, P. Caron, Z. Damianova, et al. 2020. *Research and Innovation Supporting the Farm to Fork Strategy of the European Commission* FIT4FOOD2030. https://fit4food2030.eu/reportspublications.
Zhang, X., E. A. Davidson, D. L. Mauzerall, T. D. Searchinger, P. Dumas, and Y. Shen. 2015. "Managing Nitrogen for Sustainable Development." *Nature* 528: 51–9.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Wimmer, Stefan, and K Hervé Dakpo. 2023. "Components of Agricultural Productivity Change: Replication of US Evidence and Extension to the EU." *Applied Economic Perspectives and Policy* 45(3): 1332–1355. https://doi.org/10.1002/aepp.13377