

# Chapter 17

## Nonparametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture

Christopher J. O'Donnell

**Abstract** Recent theoretical advances in total factor productivity (TFP) measurement mean that TFP indexes can now be exhaustively decomposed into unambiguous measures of technical change and efficiency change. To date, all applications of this new methodology have involved decomposing indexes that have poor theoretical properties. This article shows how the methodology can be used to decompose a new TFP index that satisfies all economically-relevant axioms from index theory. The application is to state-level data from 1960 to 2004. In most states, the main drivers of agricultural TFP change are found to have been technical change and scale and mix efficiency change.

**Keywords** Data envelopment analysis • Environmental change • Lowe index • Mix efficiency • Scale efficiency • Technical efficiency • Total factor productivity

It is difficult, if not impossible, to find coherent estimates of the technical change and efficiency change components of U.S. agricultural productivity change. Several estimates of technical change and efficiency change are available (e.g., Morrison Paul and Nehring 2005; Morrison Paul et al. 2004) but they are not coherent in the sense that they do not combine to yield recognizable productivity indexes. And while several researchers have decomposed well-known productivity indexes into various components (e.g., Capalbo 1988), not all of these components have unambiguous interpretations as measures of technical change or efficiency change. This lack of coherent information on the components of productivity change can lead to poor public policy—policy-makers cannot properly assess whether the payoffs from improving the rate of technical progress (e.g., through increased

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C.J. O'Donnell (✉)

The University of Queensland, Centre for Efficiency and Productivity Analysis,  
Brisbane, QLD 4072, Australia

e-mail: [c.odonnell1@uq.edu.au](mailto:c.odonnell1@uq.edu.au); [c.odonnell@economics.uq.edu.au](mailto:c.odonnell@economics.uq.edu.au)

R&D expenditure) are more or less likely to outweigh the payoffs from improving levels of either technical efficiency (e.g., through education and training programs) or scale and mix efficiency (e.g., by using taxes and subsidies to change relative prices). This article fills this information gap by decomposing productivity indexes for U.S. agriculture into an exhaustive set of recognizable measures of technical change, technical efficiency change, and scale and mix efficiency change.

The analysis in this article is conducted within the aggregate quantity-price framework first developed in O'Donnell (2008). In that working paper I show how carefully-defined price and quantity aggregates can be used to decompose profitability change (a measure of value change) into the product of a terms-of-trade (TT) index (a measure of price change) and a *multiplicatively-complete* total factor productivity (TFP) index (a measure of quantity change). I also show that, in theory, any multiplicatively-complete TFP index can be exhaustively decomposed into the product of a measure of technical change and several measures of efficiency change. Important features of this methodology are that it does not depend on restrictive assumptions concerning the production technology, and it does not depend on any assumptions concerning firm behaviour or the level of competition in input or output markets. To date, all empirical applications of the methodology have involved the decomposition of multiplicatively-complete Hicks-Moorsteen TFP indexes (e.g., O'Donnell 2010).

The class of multiplicatively-complete TFP indexes also includes the Laspeyres, Paasche, Fisher and Törnqvist indexes. A problem with these well-known indexes (and the Hicks-Moorsteen index) is that they fail to satisfy a commonsense transitivity axiom. Transitivity guarantees that a direct comparison of two observations (i.e., firms or periods) will yield the same estimate of TFP change as an indirect comparison through a third observation. The usual solution to the transitivity problem involves a geometric averaging procedure due to Elteto and Koves (1964) and Szulc (1964). Unfortunately, although they may be transitive, these so-called EKS indexes fail an identity axiom. The identity axiom guarantees that if outputs and inputs are unchanged then the TFP index will take the value one (i.e., indicate that productivity is also unchanged). This article proposes a new TFP index that satisfies both the transitivity axiom and the identity axiom. It then decomposes the index into technical change and efficiency change components. This article refers to the index as a Lowe TFP index because it can be written as the ratio of two indexes that have been attributed to Lowe (1823).

In practice, decomposing TFP indexes into measures of technical change and efficiency change involves estimating the production frontier. The two main approaches to estimating production frontiers are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The SFA approach is parametric in the sense that it requires parameterisation of the production frontier and various assumptions concerning the parameters of the distributions of random error terms. One of the advantages of the SFA approach is that it makes an allowance for measurement errors and other sources of statistical noise. Disadvantages of the approach are that results may be sensitive to parametric assumptions, it is difficult to identify the pure scale efficiency change and pure mix efficiency change

components of TFP change (i.e., the productivity dividends associated with changes in scale alone and changes in output mix or input mix alone), and results may be unreliable if sample sizes are small. The alternative DEA approach is commonly referred to as a nonparametric approach because it doesn't require any explicit assumptions about the functional form of the frontier (the frontier is implicitly assumed to be locally linear<sup>1</sup>) or the distributions of random error terms (all noise effects are implicitly assumed to be zero). The main advantages of the DEA approach are that there are no statistical issues (e.g., endogeneity) associated with estimating multiple-input multiple-output technologies, and it can be used to estimate levels of, and therefore changes in, pure scale efficiency. This article shows how DEA can also be used to estimate the pure mix efficiency change components of Paasche, Laspeyres, Fisher and Lowe TFP indexes. Disadvantages of the DEA approach are that it does not allow for statistical noise and so cannot distinguish inefficiency from noise, and technical efficiency estimates are upwardly biased in small samples.

The main contributions of this article are threefold. First, it defines a new TFP index (referred to as a Lowe TFP index) that satisfies all economically-relevant axioms from index number theory, including the identity and transitivity axioms. Second, it develops new linear programming methodology for exhaustively decomposing Paasche, Laspeyres, Fisher and Lowe TFP indexes into measures of technical change and various measures of technical, scale and mix efficiency change. Third, it fills an information gap by reporting a coherent set of estimates of productivity change, technical change and efficiency change in US agriculture.

The structure of the article is as follows. The first few sections explain how profitability change can be decomposed into the product of a TFP index and a TT index. Attention is focused on the Lowe TFP index because this is one of only handful of indexes that satisfy seven basic axioms from index number theory. Some time is spent explaining how the methodology I develop in O'Donnell (2008) can be used to decompose Lowe TFP indexes into measures of technical change and efficiency change. This involves the specification of new DEA problems for estimating levels of (and therefore changes in) pure technical, scale and mix efficiency. Variants of these DEA problems can also be used to estimate the maximum level of TFP possible using a production technology. The last few sections of the article describe the empirical application. The dataset is a state-level panel dataset assembled by the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA). It comprises observations on the prices and quantities of agricultural outputs and inputs in  $I = 48$  states over the  $T = 45$  years from 1960 to 2004. The penultimate section reports estimates of TFP change and various measures of efficiency change for selected states in selected periods. The final section of the article summarises the findings and offers two suggestions for further research.

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<sup>1</sup>Local linearity means the frontier is formed by a number of intersecting hyperplanes. Thus, it may be more appropriate to refer to DEA as a semiparametric rather than a nonparametric approach.

### 17.1 The Components of Profitability Change

Let  $x_{it} \in \mathfrak{R}_+^M$ ,  $q_{it} \in \mathfrak{R}_+^N$ ,  $w_{it} \in \mathfrak{R}_+^M$  and  $p_{it} \in \mathfrak{R}_+^N$  denote vectors of input and output quantities and prices for firm  $i$  in period  $t$ . In O’Donnell (2008) I define the TFP of the firm to be  $TFP_{it} = Q_{it}/X_{it}$  where  $Q_{it} \equiv Q(q_{it})$  is an aggregate output and  $X_{it} \equiv X(x_{it})$  is an aggregate input. The only requirements placed on the aggregator functions  $Q(\cdot)$  and  $X(\cdot)$  are that they be nonnegative, nondecreasing and linearly homogeneous. If TFP is defined in this way then the index that compares the TFP of firm  $i$  in period  $t$  with the TFP of firm  $h$  in period  $s$  is

$$TFPI_{hsit} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it}/X_{it}}{Q_{hs}/X_{hs}} = \frac{Q_{it}/Q_{hs}}{X_{it}/X_{hs}} = \frac{QI_{hsit}}{XI_{hsit}} \tag{17.1}$$

where  $QI_{hsit} = Q_{it}/Q_{hs}$  and  $XI_{hsit} = X_{it}/X_{hs}$  are output and input quantity indexes. Thus, within this framework, TFP growth is a measure of output growth divided by a measure of input growth, which is how productivity growth is usually defined (e.g., Griliches 1961; Jorgenson and Griliches 1967). In O’Donnell (2008) I use the term *multiplicatively-complete* to refer to TFP indexes that can be written in terms of aggregate input and output quantities as in (17.1). The Laspeyres, Paasche, Törnqvist, Hicks-Moorsteen and Fisher TFP indexes are all multiplicatively complete. Indexes that are *not* multiplicatively-complete include the widely-used output- and input-oriented Malmquist TFP indexes of Caves et al. (1982) and the lesser-known TFP index of Diewert and Morrison (1986)—except in restrictive special cases, these indexes cannot be expressed as an output quantity index divided by an input quantity index (i.e., they cannot be used to measure TFP change).

Associated with any non-zero aggregate quantities are implicit aggregate prices  $P_{it} = p'_{it}q_{it}/Q_{it}$  and  $W_{it} = w'_{it}x_{it}/X_{it}$ . The existence of these implicit prices means that profit can be written  $\pi_{it} = P_{it}Q_{it} - W_{it}X_{it}$  and profitability can be written  $PROF_{it} = (P_{it}Q_{it})/(W_{it}X_{it})$ . Furthermore, the index that compares the profitability of firm  $i$  in period  $t$  with the profitability of firm  $h$  in period  $s$  can be written

$$PROFI_{hsit} = \frac{PROF_{it}}{PROF_{hs}} = \frac{P_{it}Q_{it}}{W_{it}X_{it}} \times \frac{W_{hs}X_{hs}}{P_{hs}Q_{hs}} = \frac{PI_{hsit}}{WI_{hsit}} \times \frac{QI_{hsit}}{XI_{hsit}} = TTI_{hsit} \times TFPI_{hsit} \tag{17.2}$$

where  $PI_{hsit} = P_{it}/P_{hs}$  is an output price index,  $WI_{hsit} = W_{it}/W_{hs}$  is an input price index and  $TTI_{hsit} = PI_{hsit}/WI_{hsit}$  is a TT index measuring output price change relative to input price change. It is apparent from (17.2) that (1) if the reference and comparison firms receive the same prices for their outputs and pay the same prices for their inputs then the TT index will equal unity and any changes in profitability will be plausibly attributed entirely to changes in TFP, (2) if two firms use the same inputs to produce the same outputs then any changes in profitability will be attributed entirely to changes in prices, and (3) if profitability is constant then a TFP index can be computed as the reciprocal of a TT index.

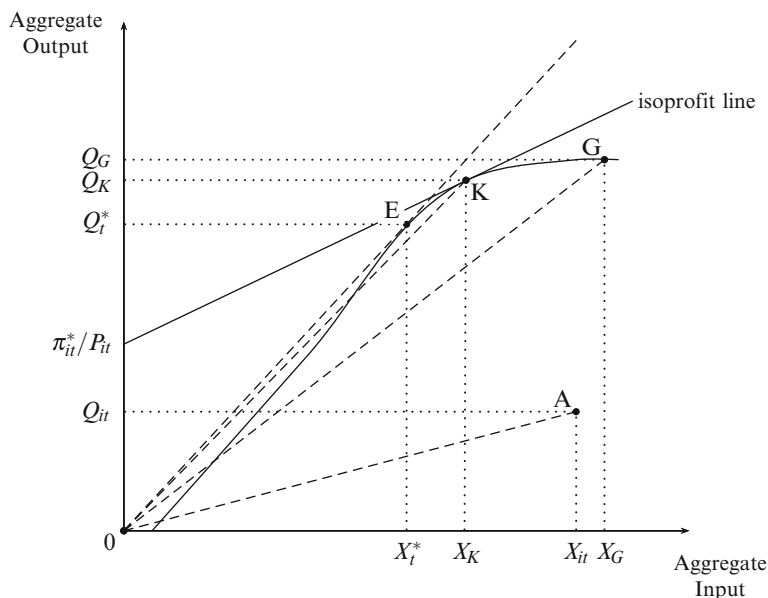


Fig. 17.1 TFP, profitability and the TT

This aggregate quantity-price framework can be used to provide important insights into the behaviour of rational profit-maximising firms. To illustrate, Fig. 17.1 depicts the aggregate output and input of firm  $i$  in period  $t$  in two dimensional-aggregate quantity space (point A). In this figure, the curve passing through points E, K and G is the boundary of the set of all aggregate-output aggregate-input combinations that are technically feasible in period  $t$ . The definition (17.1) means that the TFP of a firm operating at any point in aggregate quantity space is the slope of the ray from the origin to that point—for example, the TFP of the firm operating at point A is  $TFP_{it} = Q_{it}/X_{it} = \text{slope } 0A$ , and the TFP of the firm operating at point E is  $TFP_t^* = Q_t^*/X_t^* = \text{slope } 0E$ . The solid line passing through point K in Fig. 17.1 is an isoprofit line with slope  $-W_{it}/P_{it}$  and intercept  $\pi_{it}^*/P_{it}$ . The fact that this isoprofit line is tangent to the production frontier means that point K maximizes profit at aggregate prices  $P_{it}$  and  $W_{it}$ . For the technology represented in Fig. 17.1 (there are other technologies where this may not be true), the point of maximum profit will coincide with the point of maximum TFP if and only if the level of maximum TFP (the slope of the ray  $0E$ ) equals the reciprocal of the TT (the slope of the isoprofit line). This equality between the level of maximum TFP and the reciprocal of the TT is a characteristic of perfectly competitive markets and, in such cases, profits are zero. It is clear that a rational efficient firm having a benefit function that is increasing in net returns will be drawn away from the point of maximum TFP in response to an improvement in its TT, to a point such as K or G. The associated inequality between the TT and the level of maximum TFP is a characteristic of non-competitive markets and, in such cases, maximum profits are

strictly non-zero. Point G in Fig. 17.1 is the profit maximising solution in the limiting case where all inputs are relatively costless. For rational efficient firms, the economically feasible region of production is the region of locally-decreasing returns to scale between points E and G. Productivity falls and profits rise as rational efficient firms move optimally from point E to point G. Conversely, productivity increases and profits fall as rational efficient firms move optimally from point G to point E in response to deteriorations in their terms-of-trade.

This inverse relationship between TFP and the TT has two interesting implications. First, it provides a rationale for microeconomic reform programs designed to increase levels of competition in agricultural output and input markets—deteriorations in the TT that result from increased competition will tend to drive firms towards points of maximum TFP. Second, it may provide an explanation for convergence in rates of agricultural TFP growth in regions, states and countries that are becoming increasingly integrated and/or globalized—firms that strictly prefer more income to less and who face the same technology and prices will optimally choose to operate at the same point on the production frontier, they will make similar adjustments to their production choices in response to changes in the common TT, and they will thus experience similar rates of TFP change.

An empirical illustration of the inverse relationship between agricultural TFP and the agricultural TT is provided in Fig. 17.2. The solid lines (with or without markers) in this figure depict changes in profitability ( $\Delta PROF$ ), total factor productivity ( $\Delta TFP$ ) and the terms of trade ( $\Delta TT$ ) in Alabama over the period 1960–2004 (Alabama 1960 = 1). The TFP index (a Lowe index) indicates that TFP

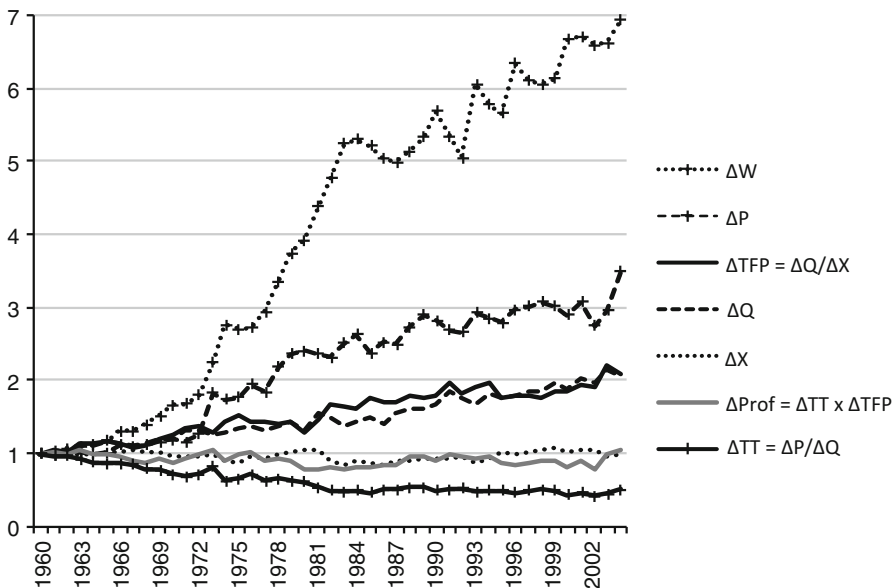


Fig. 17.2 Profitability, quantity and price change in Alabama (1960 = 1)

has more than doubled over this period. However, profitability has increased by only 4.6 % due to the offsetting effects of an estimated 49.6 % deterioration in the TT (i.e.,  $\Delta PROF = \Delta TFP \times \Delta TT = 2.076 \times 0.504 = 1.046$ ). The dashed and dotted lines without markers depict the output change ( $\Delta Q$ ) and input change ( $\Delta X$ ) components of TFP change—these series reveal that virtually all TFP growth in Alabama over the sample period has been due to output growth (i.e.,  $\Delta TFP = \Delta Q / \Delta X = 2.066 / 0.995 = 2.076$ ). The dashed and dotted lines with markers depict the associated output and input price indexes ( $\Delta P$  and  $\Delta W$ )—these series reveal that input prices have increased seven-fold over the sample period but output prices have increased by only half that amount (i.e.,  $\Delta TT = \Delta P / \Delta W = 3.493 / 6.936 = 0.504$ ). The output and input price and quantity indexes presented in Fig. 17.2 can be further decomposed into indexes that measure changes in the prices and quantities of a disaggregated set of outputs and inputs. For example, the measured increase in output prices over the sample period can be attributed to a 294 % increase in livestock prices, a 151 % increase in crop prices, and a 381 % increase in the prices of other agricultural outputs. These price increases have been associated with a 158 % increase in livestock outputs, a 30 % increase in crop outputs and a 141 % increase in other agricultural outputs. Further analysis of relationships between output and input prices and quantities at this level of disaggregation is straightforward (e.g., O'Donnell et al. 1999) but beyond the scope of this article.

## 17.2 Lowe TFP Indexes

In O'Donnell (2008) I explicitly identify the aggregator functions that underpin Laspeyres, Paasche, Fisher, Törnqvist and Hicks-Moorsteen price, quantity and TFP indexes. Unfortunately, these indexes are not generally suitable for making multitemporal (i.e., many period) or multilateral (i.e., many firm) comparisons of TFP because they violate at least one important axiom from index number theory. This article uses a very simple linear aggregator function to derive TFP indexes that satisfy all basic index number axioms. Specifically, the article aggregates outputs and inputs using the functions  $Q(q_{it}) \propto p'_0 q_{it}$  and  $X(x_{it}) \propto w'_0 x_{it}$  where  $p_0$  and  $w_0$  are pre-determined firm- and time-invariant reference prices. The associated output quantity, input quantity and TFP indexes that compare firm  $i$  in period  $t$  with firm  $h$  in period  $s$  are

$$QI_{hsit} = \frac{Q(q_{it})}{Q(q_{hs})} = \frac{p'_0 q_{it}}{p'_0 q_{hs}}, \quad (17.3)$$

$$XI_{hsit} = \frac{X(x_{it})}{X(x_{hs})} = \frac{w'_0 x_{it}}{w'_0 x_{hs}} \quad \text{and} \quad (17.4)$$

$$TFPI_{hsit} = \frac{QI_{hsit}}{XI_{hsit}} = \frac{p'_0 q_{it}}{p'_0 q_{hs}} \frac{w'_0 x_{hs}}{w'_0 x_{it}}. \quad (17.5)$$

These indices are ratios of the values of different baskets of goods evaluated at the same set of reference prices. This article refers to the TFP index (17.5) as a Lowe index because the component output and input quantity indexes given by (17.3) and (17.4) are commonly attributed to Lowe (1823) (e.g., Hill 2008).

Any number of price vectors can be used as reference price vectors  $\mathbf{p}_0$  and  $\mathbf{w}_0$  in the indexes (17.3)–(17.5). This article recommends using price vectors that are representative of the price vectors faced by all firms that are to be compared (usually all firms in the dataset).<sup>2</sup> In practice, statistical tests can be used to assess whether a chosen vector of reference prices is representative of the prices faced by any given set of firms. For example, the reference prices used for the empirical work in this article are the sample means of prices in all states in all periods (i.e.,  $\mathbf{p}_0 = \bar{\mathbf{p}} = (IT)^{-1} \sum_i \sum_t \mathbf{p}_{it}$  and  $\mathbf{w}_0 = \bar{\mathbf{w}} = (IT)^{-1} \sum_i \sum_t \mathbf{w}_{it}$ ). If observations for several more years were to become available then a simple Wald test<sup>3</sup> could be used to determine whether this same vector of reference prices was representative of prices in the larger sample.

Lowe indices satisfy a number of important axioms. To avoid repetition, this article only presents the axioms satisfied by the Lowe output quantity index (17.3). Analogous axioms are satisfied by the input quantity index (17.4) and the TFP index (17.5).

The Lowe output quantity index (17.3) is a function  $QI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_0)$  that satisfies the following commonsense axioms:

- A1** Monotonicity<sup>4</sup>:  $QI(\mathbf{q}_{hs}, \mathbf{q}_{jr}, \mathbf{p}_0) > QI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_0)$  if  $\mathbf{q}_{jr} \geq \mathbf{q}_{it}$  and  $QI(\mathbf{q}_{jr}, \mathbf{q}_{it}, \mathbf{p}_0) < QI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_0)$  if  $\mathbf{q}_{jr} \geq \mathbf{q}_{hs}$ ;
- A2** Linear homogeneity:  $QI(\mathbf{q}_{hs}, \lambda \mathbf{q}_{it}, \mathbf{p}_0) = \lambda QI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_0)$  for  $\lambda > 0$ ;
- A3** Identity:  $QI(\mathbf{q}_{it}, \mathbf{q}_{it}, \mathbf{p}_0) = 1$ ;
- A4** Homogeneity of degree zero:  $QI(\lambda \mathbf{q}_{hs}, \lambda \mathbf{q}_{it}, \mathbf{p}_0) = QI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_0)$  for  $\lambda > 0$ ;
- A5** Commensurability:  $QI(\mathbf{q}_{hs}\Lambda, \mathbf{q}_{it}\Lambda, \mathbf{p}_0\Lambda^{-1}) = QI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_0)$  where  $\Lambda$  is a diagonal matrix with diagonal elements strictly greater than zero;
- A6** Proportionality:  $QI(\mathbf{q}_{hs}, \lambda \mathbf{q}_{hs}, \mathbf{p}_0) = \lambda$  for  $\lambda > 0$ ; and
- A7** Transitivity:  $QI_{hsit} = QI_{hsjr} QI_{jrit}$ .

Axiom A1 (monotonicity) means that the index increases with increases in any element of the comparison vector  $\mathbf{q}_{it}$  and/or with decreases in any element of the reference vector  $\mathbf{q}_{hs}$ . Axiom A2 (linear homogeneity) means that a proportionate

<sup>2</sup> More precisely, reference prices should be representative of the relative importance (i.e., relative value) that decision-makers place on different outputs and inputs. Observed prices are not always the best measures of relative importance.

<sup>3</sup> For example, the prices in the larger sample could be used to test the joint null hypothesis that the population mean prices are equal to the reference prices. Such a test can be conducted in a regression framework using test commands available in standard econometrics software packages.

<sup>4</sup> Let  $q_{nit}$  denote the  $n$ th element of  $\mathbf{q}_{it}$ . The notation  $\mathbf{q}_{hs} \geq \mathbf{q}_{it}$  means that  $q_{nhs} \geq q_{nit}$  for  $n = 1, \dots, N$  and there exists at least one value  $n \in \{1, \dots, N\}$  where  $q_{nhs} > q_{nit}$ .



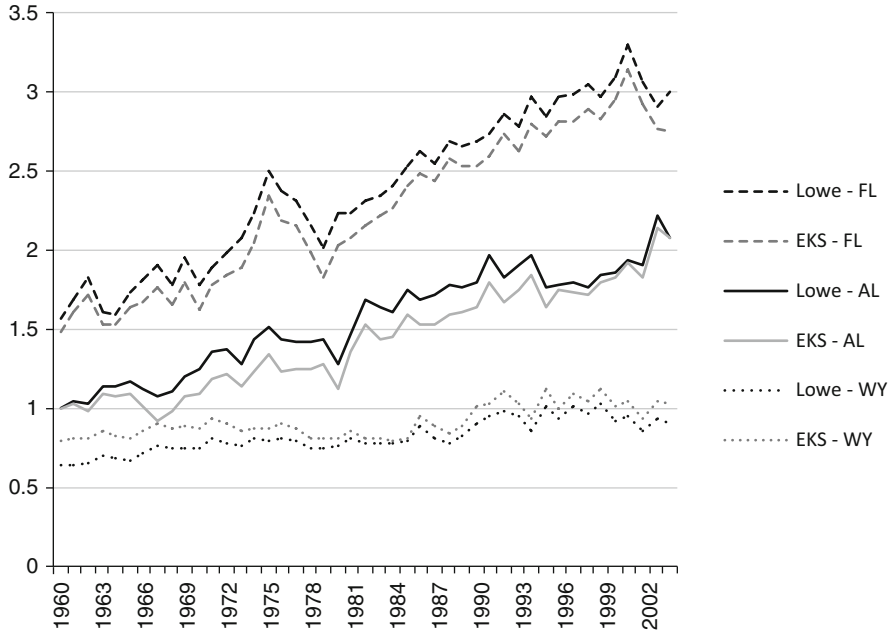
increase in the comparison vector will cause the same proportionate increase in the index. Axiom A3 (identity) means that if the comparison and reference vectors are identical then the index number takes the value one. Axiom A4 (homogeneity of degree zero) means that multiplication of the comparison and reference vectors by the same constant will leave the index number unchanged. Axiom A5 (commensurability) means that a change in the units of measurement of an output (e.g., from kilograms to tonnes) does not change the value of the index. Axiom A6 (proportionality) means that if the comparison vector is proportionate to the reference vector then the index number is equal to the factor of proportionality. Finally, A7 says the index number that directly compares the outputs of a comparison firm/period with the outputs of a reference firm/period is identical to the index number computed when the comparison is made through an intermediate firm/period.

The Laspeyres, Paasche, Fisher, Törnqvist, Hicks-Moorsteen and Lowe indexes all satisfy axioms A1–A6, but, of these indexes, only the Lowe index also satisfies the transitivity axiom A7. In practice, it is common to compute intransitive Fisher and Törnqvist indices and then address the transitivity problem by applying a geometric averaging procedure proposed by Elteto and Koves (1964) and Szulc (1964). Unfortunately, index numbers constructed using this method fail the identity axiom A3. This means that EKS indexes will almost certainly indicate increases or decreases in TFP even when input-output combinations (i.e., levels of TFP) haven't changed.

The focus of this article is first and foremost on the measurement of quantity change and TFP change. Lowe indexes are ideal for this purpose because they satisfy axioms A1–A7. However, it is worth noting that Lowe implicit indexes are less than ideal for the purpose of measuring changes in prices and the TT. For example, the implicit Lowe output price index  $PI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_{hs}, \mathbf{p}_{it}, \mathbf{p}_0) \equiv (\mathbf{p}'_{it}\mathbf{q}_{it})/\mathbf{p}'_{hs}\mathbf{q}_{hs})/(\mathbf{p}'_0\mathbf{q}_{it})/\mathbf{p}'_0\mathbf{q}_{hs})$  does not generally<sup>5</sup> satisfy price analogues of the identity and proportionality axioms A3 and A6. Implicit Laspeyres, Paasche, Fisher, Törnqvist, Hicks-Moorsteen and EKS-type price and TT indexes are also less than ideal because they also fail to satisfy at least one axiom.

To illustrate the importance of selecting a theoretically-plausible TFP index formula, Fig. 17.3 presents (implausible) EKS and (plausible) Lowe indexes of agricultural TFP change in Alabama, Florida and Wyoming over the period 1960–2004 (Alabama 1960 = 1). The grey (solid, dashed and dotted) lines in this figure are indexes computed by applying the EKS procedure to binary Fisher indexes, and the black lines are Lowe indexes defined by (17.5) (the Lowe index for Alabama was depicted earlier in Fig. 17.2). Observe that there are important differences between the two sets of estimates for particular states in particular years. For example, the EKS index indicates that in 1967 Alabama and Wyoming

<sup>5</sup> For this index, the identity axiom requires  $PI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_{it}, \mathbf{p}_{it}, \mathbf{p}_0) = 1$  while the proportionality axiom requires  $PI(\mathbf{q}_{hs}, \mathbf{q}_{it}, \mathbf{p}_{hs}, \lambda\mathbf{p}_{hs}, \mathbf{p}_0) = \lambda$  for  $\lambda > 0$ . Both axioms will be satisfied if  $\mathbf{p}_0 \propto \mathbf{p}_{hs} \propto \mathbf{p}_{it}$  (e.g., if there is no price change in the dataset and  $\mathbf{p}_0 = \bar{\mathbf{p}}$ ; or if  $\mathbf{p}_{hs} \propto \mathbf{p}_{it}$  for all  $h = 1, \dots, I$  and  $s = 1, \dots, T$  and  $\mathbf{p}_0 = \bar{\mathbf{p}}$ ).



**Fig. 17.3** TFP change in Florida, Alabama and Wyoming (Alabama 1960 = 1)

were equally productive, but the Lowe index indicates that Alabama was 39 % more productive than Wyoming.

Explaining changes in TFP over time and space involves estimating measures of technical change and efficiency change. The following section describes how multiplicatively-complete TFP indexes such as the Lowe index can be exhaustively decomposed into such measures. The EKS index cannot generally be decomposed this way because it is not multiplicatively-complete.

### 17.3 The Components of TFP Change

In O'Donnell (2008) I show that any multiplicatively-complete TFP index can be decomposed into measures of technical change and efficiency change. Among the efficiency change components are input- and output-oriented measures of technical, scale and mix efficiency change. The decomposition methodology involves identifying points of economic interest in aggregate quantity space. For illustrative purposes, consider a two-output technology and let  $\mathbf{q}_{it} = (q_{1it}, q_{2it})'$  denote the vector of outputs produced by firm  $i$  in period  $t$ . Let  $\mathbf{p}_{it} = (p_{1it}, p_{2it})'$  be the associated vector of output prices and, for a simple exposition that is consistent with the Lowe indexes presented in Fig. 17.3, let outputs be aggregated using the

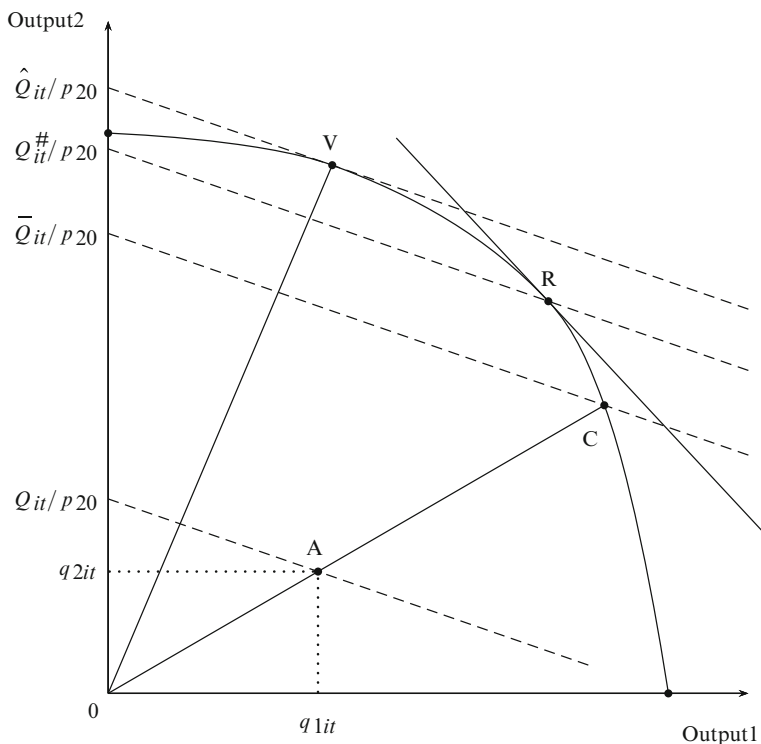


Fig. 17.4 Output-oriented measures of efficiency ( $N = 2$ )

Low output aggregator function  $Q(q_{it}) = p'_0 q_{it}$  where  $p_0 = (p_{10}, p_{20})'$ . Figure 17.4 depicts measures of technical, mix and revenue-allocative efficiency for this firm in output space: the curve passing through points V, R and C is the familiar production possibilities frontier; the solid line that is tangent to the frontier at point R is an isorevenue line with slope  $-p_{1it}/p_{2it}$ ; and the dashed line passing through point A is an iso-aggregate-output line with slope  $-p_{10}/p_{20}$  and intercept  $Q_{it}/p_{20}$ . For the firm producing  $q_{it}$ , maximising output while holding the output mix fixed involves a move from point A to point C and an increase in the aggregate output from  $Q_{it}$  to  $\bar{Q}_{it}$ , maximising revenue without any restrictions on the output mix involves a move to point R and an increase in the aggregate output to  $Q_{it}^\#$ , and maximising aggregate output without any restrictions on the output mix involves a move to point V and an increase in the aggregate output to  $\hat{Q}_{it}$ . Associated measures of efficiency are: the Farrell (1957) output-oriented measure of technical efficiency,  $OTE_{it} = Q_{it}/\bar{Q}_{it}$ ; the conventional measure of revenue-allocative efficiency,  $RAE_{it} = \bar{Q}_{it}/Q_{it}^\#$ ; and a measure of output-oriented mix efficiency first defined in O'Donnell (2008),  $OME_{it} = \bar{Q}_{it}/\hat{Q}_{it}$ .

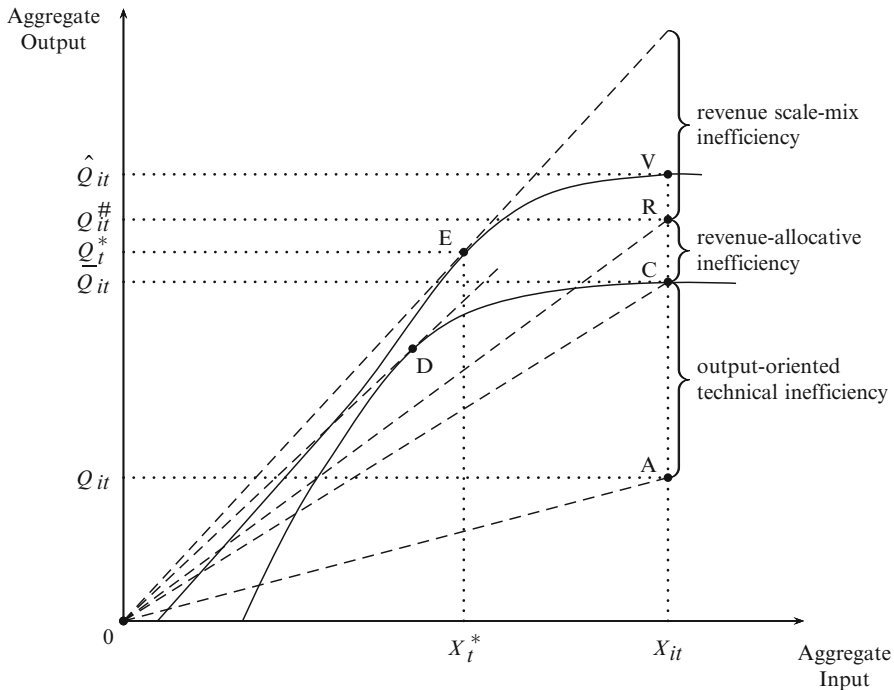


Fig. 17.5 Output-oriented measures of efficiency ( $N \geq 1$ )

Figure 17.5 maps the points A, C, R and V from Fig. 17.4 into aggregate quantity space. In this figure, the curve passing through points C and D is a *mix-restricted* frontier—this frontier envelops all technically-feasible aggregate input-output combinations that have the same input mix and output mix as the firm operating at point A. The curve passing through points V and E is the *unrestricted* production frontier depicted earlier in Fig. 17.1—this frontier envelops all aggregate input-output combinations that are feasible when all mix restrictions are relaxed. Recall that the maximum TFP that is possible using this technology is the TFP at point E:  $TFP_t^* = Q_t^*/X_t^* = \text{slope OE}$ . In O'Donnell (2008) I define TFP efficiency to be the difference between observed TFP and this maximum level of TFP:

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} = \frac{\text{slope OA}}{\text{slope OE}}. \tag{17.6}$$

It is clear from Fig. 17.5 that TFP efficiency can be decomposed as:

$$\begin{aligned} TFPE_{it} &= \frac{\text{slope OA}}{\text{slope OE}} = \frac{\text{slope OA}}{\text{slope OC}} \times \frac{\text{slope OC}}{\text{slope OR}} \times \frac{\text{slope OR}}{\text{slope OE}} \\ &= OTE_{it} \times RAE_{it} \times RSME_{it} \end{aligned} \tag{17.7}$$

where  $RSME_{it}$  = slope OR/slope OE denotes revenue-scale-mix efficiency (a measure of the difference between TFP at a revenue-allocatively efficient point and TFP at the point of maximum TFP). Other economically-meaningful decompositions of TFP efficiency include O'Donnell (2008):

$$TFPE_{it} = OTE_{it} \times OSE_{it} \times RME_{it} \quad \text{and} \quad (17.8)$$

$$TFPE_{it} = OTE_{it} \times OME_{it} \times ROSE_{it} \quad (17.9)$$

where  $OSE_{it}$  = slope OC/slope OD is the conventional measure of output-oriented scale efficiency (a measure of the difference between TFP at a technically efficient point and the maximum TFP that is possible when holding the output and input mixes fixed),  $ROSE_{it}$  = slope OV/slope OE is residual output-oriented scale efficiency (a measure of the difference between TFP at an output-mix-efficient point and the maximum possible TFP), and  $RME_{it}$  = slope OD/slope OE is residual mix efficiency (a measure of the difference between TFP at a scale-efficient point and the maximum possible TFP).

Multiplicatively-complete TFP indexes can be conveniently decomposed by rearranging Eq. (17.6) as  $TFP_{it} = TFP_t^* \times TFPE_{it}$ . A similar equation holds for firm  $h$  in period  $s$ . Thus, the TFP index defined by (17.1) can be written

$$TFPI_{hsit} = \frac{TFP_{it}}{TFP_{hs}} = \left( \frac{TFP_t^*}{TFP_s^*} \right) \left( \frac{TFPE_{it}}{TFPE_{hs}} \right). \quad (17.10)$$

The first term in parentheses is a measure of the difference in the maximum TFP possible in the two periods—this is a natural measure of technical change. Equation (17.10) reveals that TFP change can be exhaustively decomposed into a measure of technical change and a measure of efficiency change. Equations such as (17.7)–(17.9) can be used to further decompose the efficiency change component into any number of meaningful measures. For example, any multiplicatively-complete TFP index can be decomposed into measures of technical change, technical efficiency change, and a combined measure of scale and mix efficiency change:

$$TFPI_{hsit} = \frac{TFP_{it}}{TFP_{hs}} = \left( \frac{TFP_t^*}{TFP_s^*} \right) \left( \frac{OTE_{it}}{OTE_{hs}} \right) \left( \frac{OSME_{it}}{OSME_{hs}} \right) \quad (17.11)$$

where  $OSME_{it} = OSE_{it} \times RME_{it}$  denotes output-oriented scale-mix efficiency (a move from point C to point E in Fig. 17.5).

An empirical illustration of these decompositions is presented in Fig. 17.6. This figure decomposes the Lowe TFP index for Alabama (depicted earlier in Figs. 17.2 and 17.3) into an estimate of technical change ( $\Delta TFP^*$ ) and an estimate of efficiency change ( $\Delta TFPE$ ) (the DEA methodology used to obtain these estimates is discussed in the next section). Observe that TFP in Alabama increased by 107.6% over the sample period due to the combined effects of an 81.4% increase

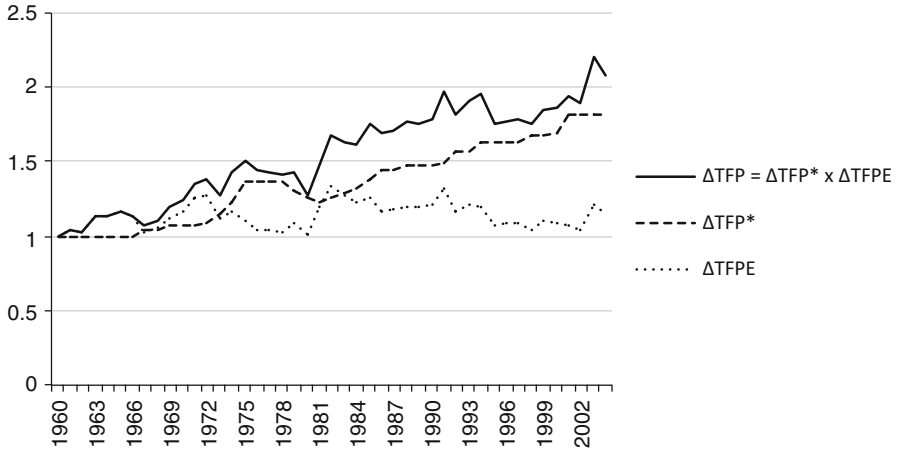


Fig. 17.6 Components of TFP change in Alabama (1960 = 1)

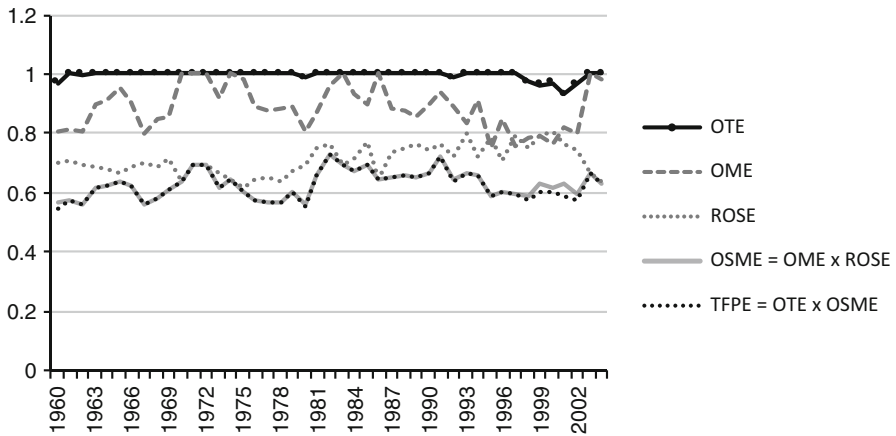


Fig. 17.7 Efficiency levels in Alabama

in the maximum TFP possible (i.e., technical change) and a 14.5% increase in overall efficiency (i.e.,  $\Delta TFP = \Delta TFP^* \times \Delta TFPE = 1.814 \times 1.145 = 2.076$ ). A further breakdown of the efficiency change component is presented in Fig. 17.7. Observe that the level of TFP efficiency in Alabama increased from 0.549 in 1960 to 0.629 in 2004 (implying  $\Delta TFPE = 0.629/0.549 = 1.145$ ). Also observe that Alabama was technically efficient but scale-mix inefficient throughout much of the sample period: in 1960 Alabama was 96.9% technically efficient but only 56.7% scale-mix efficient (i.e.,  $TFPE = OTE \times OSME = 0.969 \times 0.567 = 0.549$ ); in 2004 the state was fully technically efficient but still only 62.9% scale-mix efficient (i.e.,  $TFPE = OTE \times OSME = 1 \times 0.629 = 0.629$ ). Note that the levels of

efficiency depicted in Fig. 17.7 can also be viewed as indexes that compare efficiency levels in Alabama with efficiency levels in any state that was fully efficient in 1960 (e.g., Kansas).

### 17.4 Estimating Technical, Scale and Mix Efficiency Using DEA

The usual menu of DEA and SFA models and estimators is available for estimating the production frontiers depicted in Figs. 17.4 and 17.5. In O’Donnell (2010) I show how DEA can be used to estimate measures of technical, scale and mix efficiency associated with a Hicks-Moorsteen TFP index. This article extends that DEA methodology to the estimation of measures of efficiency associated with Paasche, Laspeyres, Fisher and Lowe TFP indexes.

A useful starting point is the well-known DEA problem for estimating the output-oriented technical efficiency of firm  $i$  in period  $t$ . If the technology exhibits variable returns to scale then an estimate of  $OTE_{it} = Q_{it}/\bar{Q}_{it}$  can be obtained by solving

$$Q_{it}/\bar{Q}_{it} = \min_{\lambda, \theta} \{ \lambda^{-1} : \lambda q_{it} \leq Q\theta; X\theta \leq x_{it}; \theta' \mathbf{1} = 1; \lambda, \theta \geq 0 \} \tag{17.12}$$

where  $Q$  is an  $N \times J_t$  matrix of observed outputs,  $X$  is an  $M \times J_t$  matrix of observed inputs,  $\theta$  is a  $J_t \times 1$  vector,  $\mathbf{1}$  is a  $J_t \times 1$  unit vector, and  $J_t$  is the number of observations used to estimate the frontier in period  $t$ . If the constraint  $\theta' \mathbf{1} = 1$  is deleted from the problem then the estimated technology will exhibit constant returns to scale. Estimates of output-oriented scale efficiency are computed by taking the ratio of the technical efficiency scores estimated under these alternative returns to scale assumptions.

To compute a measure of output-oriented mix efficiency it is convenient to first write the linear program (17.12) in the following equivalent form:

$$Q_{it}/\bar{Q}_{it} = \min_{\lambda, \theta, z} \{ Q(q_{it})/Q(z) : z \leq Q\theta; X\theta \leq x_{it}; \theta' \mathbf{1} = 1; z = \lambda q_{it}; \lambda, \theta, z \geq 0 \} \tag{17.13}$$

where  $Q(\cdot)$  is any valid output aggregator function. The equivalence of problems (17.12) and (17.13) can be established by substituting the constraint  $z = \lambda q_{it}$  into the objective function in (17.13) and noting that, since all valid aggregator functions are linearly homogeneous,  $Q(q_{it})/Q(\lambda q_{it}) = \lambda^{-1}$ . Writing (17.12) in the form of (17.13) is useful because the constraint  $z = \lambda q_{it}$  makes it explicit that estimating output-oriented technical efficiency involves estimating the maximum increase in TFP (or aggregate output) that is possible while holding the input level (and therefore the aggregate input) and the output mix fixed. Moreover, it suggests

that an estimate of the output-oriented mix efficiency of firm  $i$  in period  $t$  can be obtained by simply relaxing the mix constraint  $z = \lambda q_{it}$ . Specifically, an estimate of  $OME_{it} = \bar{Q}_{it}/\hat{Q}_{it} = (Q_{it}/\hat{Q}_{it})/(Q_{it}/\bar{Q}_{it})$  can be obtained by solving

$$Q_{it}/\hat{Q}_{it} = \min_{\theta, z} \{Q(q_{it})/Q(z) : z \leq Q\theta; X\theta \leq x_{it}; \theta'v = 1; \theta, z \geq 0\}. \quad (17.14)$$

Unlike the solution to the technical efficiency problem (17.12), the solution to the mix efficiency problem (17.14) depends on the choice of aggregator function. If interest lies in identifying the output-oriented mix efficiency change component of a particular multiplicatively-complete TFP index, then the aggregator function should be the function that underpins that index. For example, if the TFP index is a Paasche index then the aggregator function is  $Q(q_{it}) \propto p'_{it}q_{it}$  and problem (17.14) becomes

$$Q_{it}/\hat{Q}_{it} = \min_{\theta, z} \{p'_{it}q_{it}/p'_{it}z : z \leq Q\theta; X\theta \leq x_{it}; \theta'v = 1; \theta, z \geq 0\}. \quad (17.15)$$

The solution to this problem will be the ratio of observed revenue to the maximum revenue possible holding the input vector fixed (i.e., the common measure of revenue efficiency,  $RE_{it}$ ). Thus, in the special case of the Paasche TFP index, the measure of output-oriented mix efficiency is the well-known measure of revenue-allocative efficiency:  $OME_{it} = RAE_{it} = RE_{it}/OTE_{it}$ .

The TFP index proposed in this article is the Lowe index given by (17.5), underpinned by the output aggregator function  $Q(q_{it}) \propto p'_0q_{it}$ . Estimating the output mix-efficiency change component of this TFP index involves solving

$$Q_{it}/\hat{Q}_{it} = \min_{\theta, z} \{p'_0q_{it}/p'_0z : z \leq Q\theta; X\theta \leq x_{it}; \theta'v = 1; \theta, z \geq 0\}. \quad (17.16)$$

Similar problems are available for identifying the output-oriented mix efficiency levels associated with Laspeyres indexes, and for computing DEA estimates of input-oriented technical efficiency ( $ITE$ ), input-oriented mix efficiency ( $IME$ ), cost efficiency ( $CE$ ) and cost-allocative efficiency ( $CAE = CE/ITE$ ) associated with Paasche, Laspeyres and Lowe indexes. The efficiency components of the Fisher TFP index can be computed as the geometric average of the Laspeyres and Paasche measures.

### 17.5 Estimating Maximum TFP and the Rate of Technical Change

The maximum TFP possible using the production technology is the TFP at point E in Fig. 17.1:  $TFP_t^* = Q_t^*/X_t^* = \text{slope OE}$ . Points of maximum TFP can be estimated using a DEA problem that is closely related to problem (17.14).



Problem (17.14) allows outputs to vary freely but holds the input vector fixed. The point of maximum TFP can be estimated by solving a less restrictive problem that allows both inputs and outputs to vary freely:

$$TFP_t^* = \max_{\theta, z, v} \{Q(z) : z \leq Q\theta; X\theta \leq v; X(v) = 1; \theta' t = 1; \theta, z, v \geq 0\} \quad (17.17)$$

where the constraint  $X(v) = 1$  is a normalizing constraint that plays the same role as a normalizing constraint in the primal form of (17.12). Again, the solution to problem (17.17) depends on the choices of input and output aggregator functions. Again, if interest centres on identifying the technical change component of a multiplicatively-complete TFP index then the aggregator functions should be those that underpin that index. For example, if the TFP index is the Paasche index then the problem (17.17) becomes

$$TFP_t^* = \max_{\theta, z, v} \{p'_{it} z : z \leq Q\theta; X\theta \leq v; w'_{it} v = 1; \theta' t = 1; \theta, z, v \geq 0\}. \quad (17.18)$$

In this case, the optimized value of the objective function is the maximum profitability that can be achieved by firm  $i$  in period  $t$ . This level of maximum profitability is usually of considerable economic interest, but not for purposes of measuring technical change—as a measure of technical change it is implausible because it varies with observed prices, even when the production possibilities set (represented by the constraints  $z \leq Q\theta$  and  $X\theta \leq v$ ) remains unchanged (i.e., even when there is no technical change). In contrast, the technical change component of the Lowe TFP index is robust to differences in the prices faced by different firms. If the TFP index is a Lowe index then problem (17.17) becomes

$$TFP_t^* = \max_{\theta, z, v} \{p'_0 z : z \leq Q\theta; X\theta \leq v; w'_0 v = 1; \theta' t = 1; \theta, z, v \geq 0\}. \quad (17.19)$$

Variations in levels of maximum TFP are due to inward and outward movements in the production frontier in the region of local constant returns to scale (point E in Figs. 17.1 and 17.5). A common view is that these movements are due to variations in technical know-how. However, Solow (1957, p. 312) takes a broader view of technical change and attributes movements in the production frontier to variations in any factors that are not accounted for by the input and output variables that have been included in the analysis. Aside from stocks of scientific and technical knowledge, these “environmental” factors may include anything from measures of labor quality to seasonal conditions. If such environmental factors are favourable for agricultural production then the maximum output possible using any given level of included inputs is higher than the maximum output possible when environmental conditions are poor (i.e., favourable environmental conditions are a form of “technical progress”).

**Table 17.1** USDA ERS farm production regions

Region	States <sup>a</sup>	Window
1. Pacific	CA, OR, WA	5
2. Mountain	AZ, CO, ID, MT, NM, NV, UT, WY	2
3. Northern Plains	KS, ND, NE, SD	4
4. Southern Plains	OK, TX	8
5. Corn Belt	IA, IL, IN, MO, OH	3
6. Southeast	AL, FL, GA, SC	4
7. Northeast	CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT	2
8. Lake States	MI, MN, WI	5
9. Appalachian	KY, NC, TN, VA, WV	3
10. Delta States	AR, LA, MS	5

<sup>a</sup> Official US Postal Service abbreviations

To account for spatial variations in environmental factors, this article estimates separate variable returns to scale production technologies for the ten farm production regions identified by the USDA-ERS. A list of the states in each region is provided in Table 17.1. To account for temporal variations in environmental factors, these technologies have been estimated using DEA models that allow for a small amount of technical regress. This involves using a moving window of observations to estimate the technology in each region. For example, the Pacific region production technology has been estimated using a moving five-year window of observations, while the Mountain region technology has been estimated using a two-year window. The size of the window was governed by the number of states in each region and reflects a desire to estimate each regional frontier using at least twice as many observations as there are input and output variables in the dataset. The final column in Table 17.1 is the size of the window used to estimate the technology in each region.

Indexes that compare estimated levels of maximum TFP in selected regions are depicted in Fig. 17.8 (Southeast 1960 = 1). The Southeast region had the highest estimated maximum TFP of any region in both 1960 and 2004 (i.e.,  $TFP = TFP^* = 1.045$  in Alabama in 1960 and  $TFP = TFP^* = 1.896$  in Alabama in 2004). Observe from Fig. 17.8 that the maximum possible TFP in the Southeast region is estimated to have increased by 81.4 % over the sample period (i.e.,  $\Delta TFP^* = 1.896/1.045 = 1.814$ ) whereas the maximum TFP in the Southern Plains region is estimated to have increased by only 40 % [i.e.,  $\Delta TFP^* = (0.946/1.045)/(0.676/1.045) = 0.905/0.646 = 1.40$ ]. The estimated rate of technical change in the Southern Plains is lower than in the Southeast partly because large windows have the effect of dampening estimated rates of technical change. Indeed, as the size of the window approaches the time-series dimension of the dataset the estimated rate of technical change will approach zero and any TFP change will be attributed entirely to efficiency change.

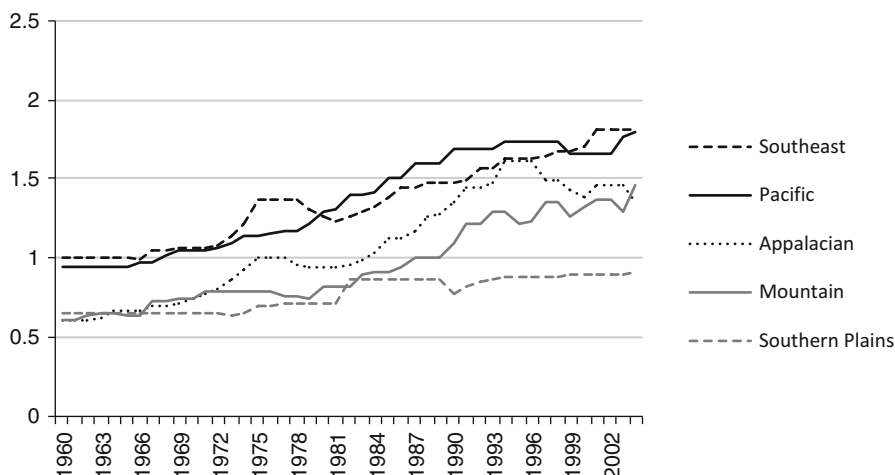


Fig. 17.8 Technical/environmental change in selected regions (Southeast 1960 = 1)

## 17.6 Data

This article uses a state-level panel dataset compiled by the ERS and recently analysed by, for example, Ball et al. (2004) and Fousekis (2007). Parts of the dataset have also been used recently by LaFrance et al. (2011). The version of the dataset used in this article extends from 1960 to 2004 and comprises observations on the prices and quantities of three outputs (livestock, crops and other outputs) and four inputs (capital, land, labor and materials) in each state in each year. Output quantities are measures of quantities sold plus on-farm consumption and net changes in inventories. Input quantities are measures of purchased inputs as well as farm production used on the farm. Output and input prices are adjusted for subsidies, taxes and direct payments under government commodity programs. Thus, they reflect the net values of outputs and inputs to farmers. The main features of the dataset are described in Ball et al. (1997).

The dataset has its shortcomings. Most importantly, the prices are multilateral price indexes constructed using binary Fisher price indexes and the EKS geometric averaging procedure (Ball et al., 2004). Thus, the price indexes are transitive but fail the identity axiom—the output and input price variables will almost certainly indicate price differences across states and/or time periods even if prices are identical. The quantities are implicit quantity indexes constructed by dividing revenues and costs by the EKS price indexes. This means they satisfy a product test. However, if the price variables do not accurately reflect temporal and spatial variations in prices (because they are intransitive) then it is unlikely that the implicit quantity variables will accurately reflect variations in quantities. Similar problems are found in other U.S. agricultural datasets. For example, the variables in the

InSTePP datasets used by Acquaye et al. (2003) and Alston et al. (2010) are constructed using binary Fisher indexes that violate the transitivity axiom.<sup>6</sup>

## 17.7 The Components of Profitability and TFP Change in US Agriculture

This section reports selected<sup>7</sup> estimates of changes in agricultural profitability, TFP and efficiency in U.S. agriculture over the 45 years from 1960 to 2004. It has already been reported that in Alabama during this period (1) estimated profitability increased by 4.6 % due to the combined effects of a  $1 - 0.504 = 49.6$  % fall in the TT and a 107.6 % increase in TFP, (2) in turn, estimated TFP increased due to an 81.4 % increase in the maximum possible TFP (i.e., “technical change”) and a 14.48 % increase in overall efficiency (from 0.549 to 0.629), and (3) in turn, estimated overall efficiency increased due to a 3.2 % increase in output-oriented technical efficiency (from 0.969 to 1) and a 10.9 % increase in output-oriented scale-mix efficiency (from 0.567 to 0.629). These estimates and others (all rounded to two decimal places) are reported in the first rows of Tables 17.2 and 17.3. The remaining rows in these tables report estimates for selected other states. The values that are marked with an “a” are the highest among the 48 states, while those marked with a “b” are the lowest among the 48 states.

The estimates reported in Tables 17.2 and 17.3 are transitive and can therefore be used to make meaningful comparisons of performance across both space and time. For example, the estimates reported in the first column of Table 17.2 reveal that in 1960 Florida was the most profitable state, New Hampshire was the least profitable, and the level of profitability in Alabama was 58 % higher than in New Hampshire ( $\Delta PROF = 1.18/0.75 = 1.58$ ). The second column reveals that by 2004 California had become the most profitable state ( $PROF = 1.49$ ) and West Virginia had become the least profitable ( $PROF = 0.55$ ). The remaining columns reveal that Georgia experienced the largest increase in profitability over the sample period (26 %) on the back of a 157 % increase in TFP, while Tennessee experienced the largest fall in profitability (– 32 %) largely as a consequence of a 60 % deterioration in the TT. Observe that California was the most productive state in 2004 ( $TFP = 1.88$ ) and Wyoming was the least productive ( $TFP = 0.52$ ). The last few columns reveal that Kansas was fully efficient in 1960 and California and Texas were fully efficient in 2004.

<sup>6</sup> Version 4 of the InSTePP dataset covers the period 1949–2002 and can be downloaded from <http://www.instepp.umn.edu/data/instepp-USAgProdAcct.html>. All variables in this dataset take the value 100 in 1949, so it cannot be used to generate TFP indexes that are comparable with the indexes depicted in Fig. 17.3.

<sup>7</sup> Estimates of profitability change, TFP change, technical change, output-oriented technical efficiency change and output-oriented scale-mix efficiency change in each state in each period are available in a supplementary appendix online.

**Table 17.2** Profitability, TFP and efficiency change

State	PROF = TT × TFP			TT			TFP			TFP*			TFPE = TFP/TFP*		
	1960	2004	Δ	1960	2004	Δ	1960	2004	Δ	1960	2004	Δ	1960	2004	Δ
AL	1.18	1.24	1.05	2.06	1.04	0.50	0.57	1.19	2.08	1.05a	1.90a	1.81	0.55	0.63	1.14
CA	1.39	1.49a	1.07	1.58	0.79	0.50	0.88	1.88a	2.14	0.99	1.88	1.91	0.89	1.00a	1.12
FL	1.72a	1.35	0.79	1.91	0.78	0.41	0.90a	1.72	1.92	1.05a	1.90a	1.81	0.86	0.91	1.06
GA	1.02	1.29	1.26a	1.73	0.85	0.49	0.59	1.51	2.57	1.05a	1.90a	1.81	0.56	0.80	1.42
KS	1.19	0.89	0.75	1.92	0.82	0.43	0.62	1.08	1.75	0.62b	1.22	1.98	1.00a	0.88	0.88
LA	1.08	0.82	0.76	2.47	0.81	0.33b	0.44	1.02	2.34	0.66	1.53	2.31	0.66	1.02	
MI	0.82	0.94	1.15	1.82	0.80	0.44	0.45	1.18	2.62	0.68	1.26	1.85	0.66	0.94	1.42
NH	0.75b	0.77	1.03	1.76	0.72	0.41	0.42	1.06	2.51	0.70	1.61	2.30	0.61	1.09	
NM	1.13	1.17	1.03	2.97a	1.36	0.46	0.38	0.86	2.27	0.64	1.53	2.40a	0.60	0.56	0.94
OH	0.76	0.82	1.08	1.38b	0.66	0.48	0.55	1.24	2.27	0.77	1.63	2.12	0.71	1.07	
OK	1.35	0.94	0.70	2.06	1.11	0.54	0.66	0.85	1.29b	0.68	0.95b	1.40b	0.97	0.89	0.92
OR	0.97	1.16	1.20	2.15	0.82	0.38	0.45	1.41	3.12a	0.99	1.88	1.91	0.46b	0.75	1.63a
RI	0.82	0.87	1.07	1.75	0.61b	0.35	0.47	1.42	3.04	0.70	1.61	2.30	0.67	1.32	
TN	1.01	0.68	0.68b	2.14	0.85	0.40	0.47	0.81	1.71	0.63	1.41	2.22	0.74	0.77	
TX	1.17	0.94	0.81	2.29	1.00	0.44	0.51	0.95	1.85	0.68	0.95b	1.40b	0.76	1.00a	1.32
WV	0.78	0.55b	0.71	2.23	0.84	0.38	0.35b	0.66	1.90	0.63	1.41	2.22	0.55	0.47	0.85
WY	1.02	0.86	0.84	2.78	1.65a	0.59a	0.37	0.52b	1.42	0.64	1.53	2.40a	0.58	0.34b	0.59b

Note: a = highest value among the 48 states; b = lowest value among the 48 states

**Table 17.3** Output-oriented components of efficiency change

State	TFPE = OTE × OSME			OTE			OSE			OME			OSME		
	1960	2004	Δ	1960	2004	Δ	1960	2004	Δ	1960	2004	Δ	1960	2004	Δ
AL	0.55	0.63	1.14	0.97	1.00a	1.03	0.98	1.00	1.02	0.80b	0.98	1.22a	0.57	0.63	1.11
CA	0.89	1.00a	1.12	1.00a	1.00a	1.00	1.00a	1.00a	1.00	1.00a	1.00a	1.00	0.89	1.00a	1.12
FL	0.86	0.91	1.06	1.00a	1.00a	1.00	1.00a	1.00a	1.00	1.00a	0.94	0.94	0.86	0.91	1.06
GA	0.56	0.80	1.42	0.89	1.00a	1.12	1.00	1.00a	1.00	0.87	1.00	1.14	0.63	0.80	1.26
KS	1.00a	0.88	0.88	1.00a	1.00	1.00	1.00a	1.00	1.00	1.00a	0.92	0.92	1.00a	0.89	0.89
LA	0.66	0.67	1.02	1.00a	1.00a	1.00	1.00a	0.90	0.90	1.00a	1.00a	1.00	0.66	0.67	1.02
MI	0.66	0.94	1.42	1.00a	1.00a	1.00	1.00a	1.00a	1.00	0.92	1.00a	1.09	0.66	0.94	1.42
NH	0.61	0.66	1.09	0.83b	1.00a	1.21a	0.96	1.00a	1.05	0.94	0.85	0.90	0.73	0.66	0.90
NM	0.60	0.56	0.94	1.00a	1.00a	1.00	1.00a	1.00a	1.00	0.99	0.85	0.86b	0.60	0.56	0.94
OH	0.71	0.76	1.07	1.00a	0.93	0.93	1.00a	0.97	0.97	1.00a	0.93	0.93	0.71	0.82	1.15
OK	0.97	0.89	0.92	1.00a	1.00a	1.00	1.00a	1.00a	1.00	1.00a	1.00a	1.00	0.97	0.89	0.92
OR	0.46b	0.75	1.63	1.00a	1.00a	1.00	0.92	1.00a	1.08	1.00a	1.00a	1.00	0.46b	0.75	1.63a
RI	0.67	0.88	1.32	1.00a	1.00a	1.00	0.89b	1.00a	1.13a	1.00a	1.00a	1.00	0.67	0.88	1.32
TN	0.74	0.57	0.77	0.98	0.99	1.01	1.00	0.99	0.99	0.86	0.78b	0.91	0.76	0.58	0.76
TX	0.76	1.00	1.32	1.00a	1.00a	1.00	1.00a	1.00a	1.00	1.00a	1.00a	1.00	0.76	1.00a	1.32
WV	0.55	0.47	0.85	1.00	1.00a	1.00	1.00	0.87	0.87	0.97	1.00a	1.03	0.55	0.47b	0.85
WY	0.58	0.34b	0.59b	1.00a	0.71b	0.71b	0.94	0.96	1.02	0.86	0.79	0.92	0.58	0.48	0.83

Note: a = highest value among the 48 states; b = lowest value among the 48 states

The output-oriented efficiency estimates reported in Table 17.3 indicate that most states were highly technically efficient throughout the sample period (exceptions include New Hampshire in 1960 and Wyoming in 2004). Output-oriented measures of pure scale efficiency and pure mix efficiency were generally high (exceptions include Rhode Island and Alabama in 1960, and Tennessee in 2004) but output-oriented measures of scale-mix efficiency were generally low (especially Oregon in 1960, and West Virginia and Wyoming in 2004). Of course, low levels of scale and/or mix efficiency are not necessarily associated with low levels of profitability (see Fig. 17.1). For example, in 2004 Alabama was one of the most profitable states ( $PROF = 1.24$ , rank 7 out of 48) and also one of the least scale-mix efficient ( $OSME = 0.63$ , rank 43).

A slightly different picture of TFP and efficiency change in U.S. agriculture is presented in Table 17.4. This table reports estimated rates of growth in TFP, maximum TFP and measures of efficiency in selected states for the sub-periods 1960–1970, 1970–1980, 1980–1990 and 1990–2002. These particular sub-periods have been chosen to facilitate comparison with estimates reported by Alston et al. (2010) and Ball et al. (1997). The average annual rate of growth in a variable  $Z$  between periods  $s$  and  $t$  can be calculated as  $\Delta \ln Z \equiv \ln(Z_t/Z_s)/(t-s)$ . For example, the average annual rate of TFP growth in Alabama in the 1960s is estimated to be  $\Delta \ln TFP = \ln(TFP_{1970}/TFP_{1960})/(1970-1960) = \ln(0.713/0.574)/10 = 0.0218$  or 2.18%, and the average annual rate of technical change is estimated to be  $\Delta \ln TFP^* = \ln(TFP_{1970}^*/TFP_{1960}^*)/10 = \ln(1.12/1.045)/10 = 0.0069$  or 0.69%. An important property of the estimated growth rates reported in Table 17.4 is that they are additive. This means, for example, that the estimated average annual rate of TFP growth in Alabama in the 1960s is equal to the sum of the technical change and efficiency change components:  $\Delta \ln TFP = \Delta \ln TFP^* + \Delta \ln OTE + \Delta \ln OSME = 0.0069 + 0.0031 + 0.0117 = 0.0218$ . It also means that estimated average annual rates of TFP and efficiency growth in US agriculture can be computed as arithmetic averages of the estimated growth rates of the 48 states—these US averages are reported in the row labeled US48 in Table 17.4.

At least three features of Table 17.4 are noteworthy. First, the average annual rate of TFP growth in US agriculture is estimated to have been 2.23% in the 1960s, 0.56% in the 1970s, 3.06% in the 1980s, and 1.01% from 1990 to 2002. These estimated rates of growth are generally quite different from the Alston et al. (2010) and Ball et al. (1997) estimates reported in the last two rows of Table 17.4. Second, the estimated average annual rate of technical change (i.e., change in maximum possible TFP) in US agriculture was 1.84% in the 1960s, 1.27% in the 1970s, 2.3% in the 1980s, and 1.38% from 1990 to 2002. These nonparametric estimates are similar to parametric estimates reported elsewhere in the literature [e.g., 1.8% reported by Ray (1982)]. Associated estimated rates of growth in output-oriented technical efficiency (0.06%, -0.18%, 0.22% and -0.02%) and output-oriented scale-mix efficiency (0.33%, -0.53%, 0.54% and -0.35%) are relatively small, indicating that technical change has been the major driver of TFP change in each sub-period.

**Table 17.4** Average annual rates of growth in TFP and efficiency (%)

State	1960-1970				1970-1980				1980-1990				1990-2002			
	TFP	TFP*	OTE	OSME	TFP	TFP*	OTE	OSME	TFP	TFP*	OTE	OSME	TFP	TFP*	OTE	OSME
AL	2.18	0.69	0.31	1.17	0.26	1.68	-0.13	-1.29	3.37	1.55	0.13	1.69	0.52	1.70	-0.29	-0.89
CA	1.85	1.07	0.00	0.78	2.47	2.09	0.00	0.38	2.67	2.67	0.00	0.00	-0.16	-0.16b	0.00	0.00
FL	1.24	0.69	0.00	0.55	2.31	1.68	0.00	0.64	1.85	1.55	0.00	0.30	1.10	1.70	-0.05	-0.55
GA	3.51	0.69	1.16a	1.66	0.71	1.68	0.00	-0.97	3.34	1.55	0.00	1.79	1.85	1.70	0.00	0.15
KS	1.51	2.24	0.00	-0.73	-0.50	0.82	-1.30	-0.02	3.33	1.99	1.30	0.03	0.21	1.19	0.00	-0.98
LA	4.87a	1.28	0.00	3.60a	-0.50	2.40	-0.76	-2.14b	3.85	2.09	0.76	1.01	-0.02	1.69	0.00	-1.71
MI	2.47	0.83	0.00	1.64	2.72a	1.38	0.00	1.34a	2.37	1.75	0.00	0.62	1.42	1.72	0.00	-0.30
NH	2.60	3.12a	0.09	-0.61	1.11	0.82	1.62a	-1.33	1.86	1.95	0.18	-0.26	1.80	1.37	0.00	0.43
NM	2.47	2.02	0.00	0.44	0.18	0.96	0.00	-0.77	2.25	2.85	-0.08	-0.52	2.38	1.93a	0.07	0.39
OH	2.16	1.28	0.00	0.88	0.97	0.51b	-0.11	0.58	2.99	2.59	0.11	0.29	0.76	1.81	0.00	-1.05
OK	-1.30b	0.00b	0.00	-1.30	1.63	1.03	0.00	0.61	1.29b	0.85b	0.00	0.43	1.26	1.20	0.00	0.06
OR	3.27	1.07	0.00	2.20	2.49	2.09	-0.24	0.64	2.35	2.67	0.24	-0.56	0.78	-0.16b	0.00	0.94a
RI	3.99	3.12a	0.00	0.87	-0.35	0.82	0.00	-1.18	5.76a	1.95	0.00	3.81a	0.23	1.37	0.00	-1.14
TN	2.00	2.03	0.18	-0.22	0.52	2.42a	-2.16	0.25	3.05	3.56a	1.92	-2.43b	-0.39	0.63	-0.60b	-0.42
TX	1.05	0.00b	0.00	1.05	0.76	1.03	-0.77	0.50	2.70	0.85b	0.77	1.08	1.31	1.20	0.00	0.11
WV	1.54	2.03	0.01	-0.49	1.81	2.42a	0.00	-0.61	3.00	3.56a	0.00	-0.57	-0.21	0.63	0.00	-0.84
WY	1.60	2.02	-1.18b	0.75	0.08	0.96	-0.89	0.02	1.80	2.85	0.85	-1.90	-0.54b	1.93a	-0.30	-2.17
US48	2.23	1.84	0.06	0.33	0.56	1.27	-0.18	-0.53	3.06	2.30	0.22	0.54	1.01	1.38	-0.02	-0.35
A	2.23	1.64	0.03	0.56	0.56	2.47	-0.44	-1.47	3.06	2.67	0.13	0.27	1.01	-0.05	-0.06	1.12
B	2.23	0.00	-0.32	2.55	0.56	0.00	-0.76	1.32	3.06	0.00	2.16	0.89	1.01	0.00	0.76	0.25
Alston	1.69				2.46				2.07				0.97			
Ball	1.91				1.22				3.36							

Note: a = highest value among the 48 states; b = lowest value among the 48 states



Finally, this article has used the term “technical change” to refer to both spatial and temporal variations in the production environment. To accommodate this broad concept of technical change, ten different production frontiers (one for each ERS farm production region) were estimated in each time period. A common alternative estimation approach involves estimating a single frontier in each period—such a model allows for temporal variations in the production environment, but does not allow for spatial variations. Estimates of TFP and efficiency change obtained using this more restrictive “Model A” are summarized in row A in Table 17.4. Unlike some other TFP indexes (e.g., the Malmquist, Hicks-Moorsteen and Diewert-Morrison indexes), the Lowe TFP index can be computed without knowing (or assuming) anything about the production technology. Thus, different restrictions on the nature of technical change will only affect the estimated technical change and efficiency change components of TFP change (i.e., the TFP index itself will remain unaffected). The results from Model A reported in Table 17.4 indicate that prior to 1990 technical progress was the most important driver of TFP growth in U.S. agriculture. However, after 1990 output-oriented scale-efficiency change became the most important driver. An even more restrictive model is a “no technical change” model that involves using all the observations in the dataset to estimate a single frontier. Results obtained using this “Model B” are summarized in row B in Table 17.4. By design, Model B attributes all TFP growth to improvements in various types of efficiency—this model suggests that prior to 1980 the main driver of TFP change was scale-mix efficiency change; after 1980 it was technical efficiency change. A discussion of statistical methods for choosing between different types of models is beyond the scope of this article.

## 17.8 Conclusion

This article uses an aggregate quantity-price framework to decompose agricultural profitability change into a measure of TFP change and a measure of change in the agricultural TT. It argues that deteriorations in the (expected) TT will generally be associated with improvements in agricultural TFP. To illustrate, the article estimates that, over the period 1960–2004, a 50 % decline in the agricultural TT in Alabama has been associated with a two-fold increase in TFP.

Well-known measures of TFP change include Laspeyres, Paasche, Fisher and Törnqvist TFP indexes. A problem with these indexes is that they fail a common-sense transitivity axiom. The usual way around the problem is to apply a geometric averaging procedure known as the EKS method. Unfortunately, so-called EKS indexes fail an identity axiom. This article proposes a new Lowe TFP index that satisfies both the transitivity and identity axioms. It also demonstrates that the choice of index formula matters—in one instance the EKS index indicates that two states were equally productive but the Lowe index indicates that one state was 39 % more productive than the other.

The Lowe index is a member of the class of multiplicatively-complete TFP indexes. In O'Donnell (2008) I demonstrate that, in theory, all such indexes can be exhaustively decomposed into a measure of technical change and various measures of technical, scale and mix efficiency change. Technical change is a measure of movements in the production frontier, technical efficiency change is a measure of movements towards the frontier, and scale and mix efficiency change are measures of movements around the frontier surface to capture economies of scale and scope. This article shows how the methodology can be used to decompose the Lowe TFP index. It finds that the main driver of TFP change in U.S. agriculture over the sample period has been technical progress (e.g., at an annual average rate of 1.84 % in the 1960s and 2.30 % in the 1990s), that levels of technical efficiency have been stable and high (e.g., the geometric mean of all  $it = 2160$  OTE estimates is 0.989), and that levels of scale-mix efficiency have been highly variable and relatively low (e.g., the geometric mean of the OSME estimates is 0.791). These findings support the view that research and development expenditure has led to expansions in the production possibilities set, that U.S. farmers adopt new technologies quickly and make relatively few mistakes in the production process, and that they rationally adjust the scale and scope of their operations in response to changes in prices and other production incentives.

Further research in at least two areas is needed to substantiate these general findings. First, there is a need to re-evaluate the index number methods that are used to construct price and quantity variables at disaggregated levels. The (binary) Fisher and Törnqvist indexes that are currently used to construct agricultural datasets (including the dataset used in this article) are no better suited to constructing (multilateral) indexes of livestock and crop outputs, for example, than they are to constructing (multilateral) indexes of aggregate output or TFP. Second, non-parametric and/or parametric statistical procedures (e.g., bootstrapping, hypothesis tests) should be used to assess the plausibility of different assumptions concerning the production technology and the nature of technical change. These assumptions play a key role in identifying the components of TFP change that policy-makers need. For example, a constant returns to scale assumption is enough to rule out any estimated TFP gains associated with improvements in scale efficiency, estimation of an average production function rather than a frontier function is enough to rule out any estimated TFP gains associated with improvements in technical efficiency, and this article has shown how different assumptions concerning changes in the production environment can be used to partially or totally eliminate the estimated TFP gains associated with technical change.

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