European Journal of Operational Research 241 (2015) 555–563

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Interfaces with Other Disciplines

Primal and dual dynamic Luenberger productivity indicators

Alfons Oude Lansink*, Spiro Stefanou, Teresa Serra

Wageningen University, Department of Business Economics, Hollandseweg 1, 6706 KN Wageningen, Netherlands

ARTICLE INFO

Article history:
Received 6 November 2013
Accepted 5 September 2014
Available online 30 September 2014

Keywords:
Directional distance function
Dynamics
Luenberger
Dairy sector
Productivity

ABSTRACT

This paper develops primal and dual versions of the dynamic Luenberger productivity growth measures that are based on the dynamic directional distance function and intertemporal cost minimization, respectively. The empirical application focuses on panel data of Dutch dairy farms over the period 1995–2005. Primal dynamic Luenberger productivity growth averages 1.5 percent annually in the period under investigation, with technical change being the main driver of annual change. Dual dynamic Luenberger productivity growth is −0.1 percent in the same period. Improvements in technical inefficiency and technical change are partly counteracted by deteriorations of allocative inefficiency, with large dairy farms presenting a slightly higher productivity growth than small dairy farms.

1. Introduction

The characterization and measurement of economic performance in both theory and practice continues to claim considerable attention in the literature. The major attention of economic performance centers on the measurement of efficiency and productivity growth. The economics literature on efficiency has produced a wide range of productivity growth measures (see Balk, 2008 for a comprehensive treatment).

The setting of the decision environment plays a crucial role in the modeling framework and the characterization of results. The static models of production are based on the firm's ability to adjust instantaneously and ignore the potential dynamic linkages of production decisions. The business policy relevance to distinguishing between the contributions of variable and capital factors to inefficiency or productivity growth is clear. For example, when variable factor use is not meeting its potential, remedies can include better monitoring of resource use; when asset use is not meeting potential, remedies can include training programs to enhance performance or even a review of the organization of assets in the production process to take advantage of asset utilization. The weakness underlying the static theory of production in explaining how some inputs are gradually adjusted has led to the development of the dynamic models of production where current production decisions constrain or enhance future production possibilities.

Allowing for the presence of dynamic adjustment leads productivity growth measurement to include a scale and technical change effects (as in the static theory) in addition to capital stock adjustment and the impact of the changing shadow values on long-run equilibrium capital stocks and investment (Luh & Stefanou, 1991). This decomposition can be further elaborated to account for efficiency change (Rungsuriyawiboon & Stefanou, 2008).

The characterization of dynamic efficiency can also build on the adjustment cost framework that implicitly measures inefficiency as a temporal concept as it accounts for the sluggish adjustment of some factors. In a nonparametric setting, Silva and Stefanou (2007) develop a myriad of efficiency measures associated with the dynamic generalization of the dual-based revealed preference approach to production analysis found in Silva and Stefanou (2003). In a parametric setting, Rungsuriyawiboon and Stefanou (2007) present and estimate the dynamic shadow price approach to dynamic cost minimization.

An intriguing prospect is to incorporate the properties of the dynamic production technology presented in Silva and Stefanou (2003) into the directional distance function framework, which can exploit the Luenberger productivity growth measurement. The directional distance function offers the powerful advantage of focusing on changes in input and output bundles, inefficiency and the technology. Such a productivity measure based on the directional distance function has its origins in Chambers, Chung, and Färe (1996) who defined a Luenberger indicator of productivity growth in the static context. A growing literature employing this approach has emerged more recently (see Balk, 2008; Boussemart, Briec, Kerstens, & Poutineau, 2003; Briec & Kerstens, 2004; Chambers & Pope, 1996; Chambers et al., 1996; Färe & Grosskopf, 2005; Färe & Primont, 2003). The dual approach to measuring Luenberger productivity growth in the static context has been elaborated by e.g. Färe, Grosskopf, and Margaritis (2008), but has hardly been applied in the literature.

* Corresponding author. Tel.: +31612395145.
E-mail address: alfons.oudelansink@wur.nl (A. O. Lansink).

http://dx.doi.org/10.1016/j.ejor.2014.09.027

This paper develops primal and dual dynamic Luenberger productivity growth indicators that are based on the dynamic directional distance function and the intertemporal cost function, respectively. The adverbs 'primal' and 'dual' refer to the models that are underlying the computation of the productivity indicators, i.e. the intertemporal cost function used for computing the dual dynamic Luenberger productivity growth indicator is dual to the primal distance function that underlies the computation of the primal dynamic Luenberger productivity growth indicator. The primal Luenberger productivity growth indicator is decomposed to identify the contributions of efficiency growth and technical change, while the dual Luenberger productivity growth indicator offers a further decomposition to identify the impact of quasi-fixed factor disequilibrium and allocative efficiency change. An illustration of these measures is applied to a panel of Dutch dairy farms over 1995–2005.

The next section develops the primal and dual measures of dynamic productivity growth and its decomposition. This is followed by the empirical application to the panel of Dutch dairy farms which uses the results of a previously estimated dynamic directional distance function found in Serra, Oude Lansink, and Stefanou (2011) to generate the primal and dual measures of productivity growth and their respective decompositions. The final section offers concluding comments.

2. The primal Luenberger indicator of dynamic productivity growth

The primal Luenberger indicator of dynamic productivity growth is defined through a dynamic directional distance function. Let $\mathbf{y}_t \in \Re^M_{++}$ represent a vector of outputs at time t, $\mathbf{x}_t \in \Re^N_+$ denote a vector of variable inputs, $\mathbf{K}_t \in \Re^F_{++}$ the capital stock vector, $\mathbf{I_t} \in \Re^F_+$ the vector of gross investments and $\mathbf{L}_t \in \Re^C_{++}$ a vector of fixed inputs for which no investments are allowed. The production input requirement set can be represented as $V_t(\mathbf{y}_t : \mathbf{K}_t, \mathbf{L}_t) = \{(\mathbf{x}_t, \mathbf{I}_t) : (\mathbf{x}_t, \mathbf{I}_t) \text{ can produce } \mathbf{y}_t \text{ given } \mathbf{K}_t, \mathbf{L}_t\}$. The input requirement set is defined by Silva and Stefanou (2003) and assumed to have the following properties: $V_t(\mathbf{y}_t : \mathbf{K}_t, \mathbf{L}_t)$ is a closed and nonempty set, has a lower bound, is positive monotonic in $\mathbf{x}_t$, negative monotonic in $\mathbf{I}_t$, is a strictly convex set, output levels increase with the stock of capital and quasi-fixed inputs and are freely disposable.

The input-oriented dynamic directional distance function $\vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})$ can be defined as follows:

$$\begin{aligned}&\vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})\\ &\quad = \max\{\beta \in \Re : (\mathbf{x}_t - \beta\mathbf{g_x}, \mathbf{I}_t + \beta\mathbf{g_I}) \in V_t(\mathbf{y}_t : \mathbf{K}_t, \mathbf{L}_t)\},\\ &\mathbf{g_x} \in \Re^N_{++},\ \mathbf{g_I} \in \Re^F_{++},\ (\mathbf{g_x}, \mathbf{g_I}) \neq (\mathbf{0}^N, \mathbf{0}^F) \end{aligned} \tag{1}$$

if $(\mathbf{x}_t - \beta\mathbf{g_x}, \mathbf{I}_t + \beta\mathbf{g_I}) \in V_t(\mathbf{y}_t : \mathbf{K}_t, \mathbf{L}_t)$ for some β, $\vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I}) = -\infty$, otherwise. The distance function is a measure of the maximal translation of $(\mathbf{x}_t, \mathbf{I}_t)$ in the direction defined by the vector $(\mathbf{g_x}, \mathbf{g_I})$, that keeps the translated input combination interior to the set $V_t(\mathbf{y}_t : \mathbf{K}_t, \mathbf{L}_t)$. Since $\beta\mathbf{g_x}$ is subtracted from $\mathbf{x}_t$ and $\beta\mathbf{g_I}$ is added to $\mathbf{I}_t$, the directional distance function is defined by simultaneously contracting variable inputs and expanding gross investments. As shown by Silva, Oude Lansink, and Stefanou (2009), $\vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I}) \geq 0$ fully characterizes the input requirement set $V_t(\mathbf{y}_t : \mathbf{K}_t, \mathbf{L}_t)$, being thus an alternative primal representation of the adjustment cost production technology.

Extending the Luenberger indicator of productivity growth defined by Chambers et al. (1996) to the dynamic setting by using the dynamic directional distance function (assuming Variable Returns to Scale) leads to:

$$\begin{aligned}\mathrm{LP}(\cdot) = \frac{1}{2}\Big\{&\Big[\vec{D}^i_{t+1}(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t\mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})\\ &- \vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}\mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I})\Big]\\ &+ \Big[\vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t\mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g_I})\\ &- \vec{D}^i_t(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}\mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I})\Big]\Big\}\end{aligned} \tag{2}$$

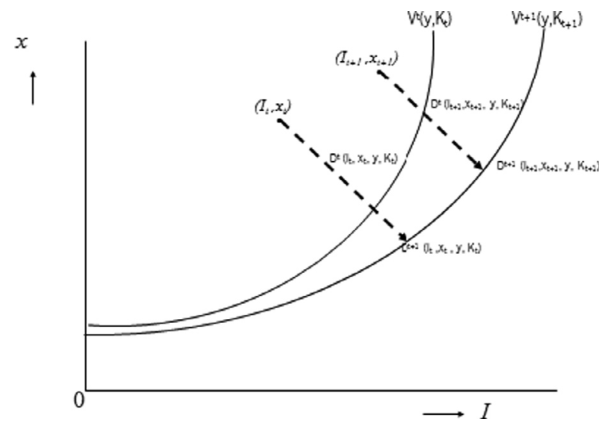

Fig. 1. Luenberger indicator of dynamic productivity growth.

This indicator provides the arithmetic average of productivity change measured by the technology at time $t + 1$ [the first two terms in Eq. (2)] and the productivity change measured by the technology at time t [the last two terms in Eq. (2)].

The Luenberger indicator of dynamic productivity growth is illustrated graphically in Fig. 1 (for ease of exposition, it is assumed that output is the same in both periods; the capital stock K differs across periods). The quantities of inputs and investments at time t and time $t+1$ are denoted as $(\mathbf{x}_t, \mathbf{I}_t)$ and $(\mathbf{x}_{t+1}, \mathbf{I}_{t+1})$, respectively. The dynamic directional distance function measures the distance to the isoquants at time t and time $t+1$, which is denoted as $\vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})$. The Luenberger indicator of dynamic productivity growth can be decomposed into the contributions of technical inefficiency change (ΔTEI) and technical change (ΔT):

$$\mathrm{LP}(\cdot) = \Delta T + \Delta\mathrm{TEI} \tag{3}$$

The decomposition of productivity growth is obtained from Eq. (2) by adding and subtracting the term $[\vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I}) - \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})]$. Technical change is computed as the arithmetic average of the difference between the technology (represented by the frontier) at time t and time $t+1$, evaluated using quantities at time t [first two terms in Eq. (4)] and time $t+1$ [last two terms in Eq. (4)]:

$$\Delta T = \frac{1}{2}\left\{\begin{aligned}&[\vec{D}^i_{t+1}(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})\\ &\quad - \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})]\\ &\quad + [\vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I})\\ &\quad - \vec{D}^i_t(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I})]\end{aligned}\right\} \tag{4}$$

Technical change can be seen in Fig. 1 as the average distance between the two isoquants. This involves evaluating the isoquants using quantities at time t, $\vec{D}^i_{t+1}(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I}) - \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})$, and quantities at time $t+1$, $\vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I}) - \vec{D}^i_t(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I})$. Dynamic technical inefficiency change is the difference between the value of the dynamic directional distance function at time t and time $t+1$:

$$\begin{aligned}\Delta\mathrm{TEI} = &\ \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})\\ &- \vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I})\end{aligned} \tag{5}$$

Technical inefficiency change is easily seen from Fig. 1 as the difference between the distance functions evaluated using quantities and technologies in period t and period $t + 1$.