Dynamic Efficiency Analysis using a Directional Distance Function

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1. Introduction

A few studies modelling some dynamic aspects of production in a nonparametric framework have been emerging in the production literature over the last decade. Sengupta (1995) uses the first-order conditions of dynamic optimisation to generate a dynamic Data Envelopment Analysis (DEA) model. In the context of the adjustment-cost theory of investment, Nemoto and Goto (1999, 2003) present dynamic efficiency measures by treating the stock of capital at the end of the period as an output and incorporate it in the conventional DEA model. Silva and Stefanou (2003) develop a nonparametric revealed preference approach to the dynamic theory of production in the context of an adjustment-cost technology and intertemporal cost minimization. Using this theoretical framework, Silva and Stefanou (2004) propose lower and upper bounds on input-based dynamic measures of technical, allocative and cost efficiency.

Besides the introduction of dynamic aspects of production in efficiency analysis, extensions of the Farrell technical efficiency measures have also emerged recently [e.g., Briec (1997), Bogetoft and Hougaard (1998), Chambers, Chung and Färe (1996, 1998), Chavas and Cox (1999), Halme *et al.* (1999)]. Exploring the relation between Shephard′s input distance function (1953) and Luenberger′s benefit function (1992), Chambers, Chung and Färe (1996) propose the directional input distance function and show the duality between this function and the cost function. Chambers, Chung and Färe (1998) propose a directional technology distance function and demonstrate the relationship between this function and Shephard′s input and output distance functions, McFadden′s gauge function and the directional input distance function. Furthermore, the duality between the directional technology distance function and the profit function is established and efficiency measures are developed (Chambers, Chung and Fare, 1998).

In this paper, we propose input-based dynamic efficiency measures using the theoretical framework proposed by Silva and Stefanou (2003) and a directional input distance function approach. A dynamic input directional distance function can be generated from an adjustment-cost technology where the dynamics are explicitly incorporated in the form of the properties of the input requirement sets with respect to the quasi-fixed factors. The properties of the dynamic input directional distance

function are inherited from the properties of the technology as in the static framework. Properties of the adjustment-cost technology are presented in Silva and Stefanou (2003). Following a similar procedure as Chambers, Chung and Färe (1998) and Färe and Grosskopf (2000) propose in the static context, dynamic input efficiency measures can be generated from the adjustment-cost directional input distance function and the dual relation between this function and the dynamic cost function. These efficiency measures are applied to a panel data set of Dutch glasshouse horticulture firms in the period 1991-1995.

The paper proceeds as follows. Section 2 presents the short- and long-run dynamic input efficiency measures. Section 3 describes the data and the empirical results are discussed in section 4. Finally, section 5 concludes.

2. Dynamic Efficiency Measurement

A directional distance function approach is used to measure dynamic efficiency in the short- and long-run. Short-run efficiency involves measuring the efficiency of variable inputs, given the quasi-fixed factors. Long-run efficiency consists in evaluating the efficiency of all factors of production and the efficiency of quasi-fixed factors, given the optimal level of variable inputs.

2.1 Short-run Efficiency

The directional variable input distance function is given as

(1) $\overrightarrow{D_{vi}}(y(t), x(t), I(t), k(t); -g_x, 0_H) = \sup\{q_x(t): (x(t) - q_x(t)g_x, I(t)) \in V(y(t): k(t))\}$

with $\overrightarrow{D_{vi}}(y(t), x(t), I(t), k(t); -g_x, 0_H) \geq 0$. $y(t)$ is the ($Mx1$)-output vector at time t, $x(t)$ is the ($Vx1$)-variable input vector, $I(t)$ is the ($Hx1$) gross investment vector, $k(t)$ is the ($Hx1$) initial capital stock vector at time period t, and ($-g_x$) is a directional vector in which the variable input vector $x(t)$ is projected onto the boundary of $V(y(t): k(t))$ at $(x(t) - q_x(t)g_x)$, $g_x \in \Re_+^V$ and $g_x \neq 0_V$. $V(y(t): k(t))$ is the input requirement set for $y(t)$

given $k(t)$. The properties of $\overrightarrow{D_{vi}}(.)$ encompasses the properties of the directional input distance function presented in Chambers, Chung and Färe (1996) plus two other properties: $\overrightarrow{D_{vi}}(.)$ is non-increasing in $I(t)$ and non-decreasing in $k(t)$.[1]

The directional variable input distance can be interpreted as the number of times the input bundle g_x is overused in $x(t)$. The directional vector must be chosen. In practice, the observed variable input vector can be chosen; implying the direction of the scaling is determined by the observed variable input mix.

Using DEA, the directional variable input distance function can be generated for each observation as follows:

(2)

$$\overrightarrow{D_{vi}}(y^i(t), x^i(t), I^i(t), k^i(t); -g_x, 0_H) = \max_{q_x, \lambda^j(t)} q_x(t)$$

$$s.t$$

$$y^i_m(t) \le \sum_{j=1}^{N} \lambda^j(t) y^j_m(t), \ m = 1,...,M;$$

$$\sum_{j=1}^{N} \lambda^j(t) x^j_v(t) \le x^i_v(t) - q_x(t) g_x, \ v = 1,...,V;$$

$$I^i_h(t) - \delta_h k^i(t) \le \sum_{j=1}^{N} \lambda^j(t)(I^j_h(t) - \delta_h k^j_h(t)), \ h = 1,...,H;$$

$$\sum_{j=1}^{N} \lambda^j(t) = 1; \ \lambda^j(t) \ge 0, \ j = 1,...,N$$

where λ is the ($Nx1$) intensity vector, δ_h is the constant depreciation rate of the quasi-fixed factor h, $h=1,...,H$, and all the other variables are defined as before.

A variable cost efficiency measure can be generated as

(3)
$$OE_x(t) = \frac{w(t)'x(t) - C(w(t), I(t), k(t), y(t))}{w(t)'g_x}$$

$$= \overrightarrow{D_{vi}}(y(t), x(t), I(t), k(t); -g_x, 0_H) + AE_x(t)$$

where $OE_x(t) \ge 0$, $w(t)$ is the ($Vx1$) variable input price vector, $C(...)$ is the short-run variable cost function and AE_x is the allocative efficiency of variable inputs.

Using DEA, the variable cost function for each firm can be generated as

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[1] Proofs of these properties will be included in a more complete version of this paper.

$$C(w^i(t), I^i(t), k^i(t), y^i(t)) = \min_{x_v(t), l^j(t)} w^i(t)'x(t)$$

$$s.t$$

$$(4)$$

$$\sum_{j=1}^{N} l^j(t)y_m^j(t) \geq y_m^i(t), \ m = 1,..., M;$$

$$x_v(t) \geq \sum_{j=1}^{N} l^j(t)x_v^j(t), \ v = 1,..., V;$$

$$\sum_{j=1}^{N} l^j(t)(I_h^j(t) - d_h k_h^j(t)) \geq I_h^i(t) - d_h k^i(t), \ h = 1,..., H;$$

$$\sum_{j=1}^{N} l^j(t) = 1; \ l^j(t) \geq 0, \ j = 1,..., N$$

Given $C(...)$ in (4) for each observation, $AE_x(t)$ is determined residually for each firm using (3).

The cost efficiency of variable inputs in (3) can also be decomposed as follows:

$$(5) \quad OE_x(t) = \frac{w(t)'x(t) - w(t)'x*(t)}{w(t)'g_x} = \frac{\sum_{v=1}^{V} w_v(t)(x_v(t) - x_v^*(t))}{w(t)'g_x} = \sum_{v=1}^{V} OE_v(t)$$

where $x^*(t)$ is the optimal variable input vector determined in (4) and $OE_v(t)$ is the cost efficiency of the variable input v, $v=1,...,V$.

The decomposition in (5) allows identifying which variable inputs are overused or underused. $OE_v(t)$ can be zero, negative or positive. The cost efficiency of the V inputs can be all zero or all positive. However, $OE_v(t)$ cannot be all negative because if $x_v(t) < x_v^*(t), \ \forall v$, then $x(t) \notin V(y(t): k(t))$.

2.2 Long-run Efficiency

The directional input distance function representing the efficiency of all factors of production is given by:

(6)

$$\vec{D}_i(y(t), x(t), I(t), k(t); -g_x, g_I) = \sup\left\{ q(t): (x(t) - q(t)g_x, I(t) + q(t)g_I) \in V(y(t): k(t)) \right\}$$

with $\vec{D}_i(y(t), x(t), I(t), k(t); -g_x, g_I) \geq 0$. The directional vector $g = (-g_x, g_I)$ projects the input vector $(x(t), I(t))$ onto the boundary of $V(y(t): k(t))$ at $(x(t) - q(t)g_x, I(t) + q(t)g_I)$, $g_x \in \Re_+^V$, $g_I \in \Re_+^H$, and $g \neq 0_{V+H}$. The directional distance function $\vec{D}_i(.)$ satisfies an extended version of the properties of the directional input distance function presented in Chambers, Chung and Färe (1996). In particular, $\vec{D}_i(.)$ is concave in $(x(t), I(t))$ and non-decreasing in $k(t)$.[2]

Using DEA, the directional input distance function can be generated for each observation as follows:

(7)

$$\vec{D}_i(y^i(t), x^i(t), I^i(t), k^i(t); -g_x, g_I) = \max_{q, I^j(t)} q(t)$$

$$s.t$$

$$y_m^i(t) \leq \sum_{j=1}^N I^j(t) y_m^j(t), \ m = 1,...,M;$$

$$\sum_{j=1}^N I^j(t) x_v^j(t) \leq x_v^i(t) - q(t)g_x, \ v = 1,...,V;$$

$$I_h^i(t) + q(t)g_I - d_h k^i(t) \leq \sum_{j=1}^N I^j(t)(I_h^j(t) - d_h k_h^j(t)), \ h = 1,...,H;$$

$$\sum_{j=1}^N I^j(t) = 1; \ I^j(t) \geq 0, \ j = 1,...,N$$

In practice, the directional vector $g = (-g_x, g_I)$ can be the observed input vector $(x^i(t), I^i(t))$.

Cost efficiency of all inputs can be expressed as

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[2] Properties of the distance function and proofs will be presented in a later version of this manuscript.

$$OE_i(t) = \frac{w(t)'x(t) + c(t)'k(t) + W_k(t)'(I(t) - \mathrm{d}\,\acute{k}(t)) - rW(w(t),c(t),k(t),y(t))}{w(t)'g_x - W_k(t)'g_I}$$

(8)

$$= \vec{D}_i(y(t),x(t),I(t),k(t);-g_x,g_I) + AE_i(t)$$

where $OE_i(t) \geq 0$, $rW(w(t),c(t),k(t),y(t))$ is the long-run cost function in flow terms or the shadow cost function and AE_i is the allocative efficiency of all inputs.

The short-run variable cost in (4) and the efficiency measures for variable inputs depend on observed variables $(w^i(t),y^i(t),x^i(t),I^i(t),k^i(t))$. In contrast, the long-run dynamic cost depends additionally on the underlying shadow value of capital. The shadow value of capital is an endogenous variable, thus it is estimated simultaneously with the long-run shadow cost using mathematical programming techniques. Following Silva and Stefanou (2004), the Linear Complementarity Problem (LCP) can be used to generate the long-run shadow cost.

Using DEA, the shadow cost for each observation can be generated as

(9)

$$rW(w^i(t),c^i(t),k^i(t),y^i(t)) = \min_{x(t),I(t),\lambda(t)} \; w^i(t)'x(t) + c^i(t)'k^i(t) + W_k^i(t)'(I(t) - \mathrm{d}\,\acute{k}^i(t))$$

$$s.t.$$

$$\sum_{j=1}^{N} \lambda^j(t)y_m^j(t) \geq y_m^i(t), \; m = 1,...,M;$$

$$x_v(t) \geq \sum_{j=1}^{N} \lambda^j(t)x_v^j(t), \; v = 1,...,V;$$

$$\sum_{j=1}^{N} \lambda^j(t)(I_h^j(t) - \mathrm{d}_h k_h^j(t)) \geq I_h(t) - \mathrm{d}_h k_h^i(t)), \; h = 1,...,H;$$

$$\sum_{j=1}^{N} \lambda^j(t) = 1, \; \lambda^j(t) \geq 0, \; j = 1,...,N$$

$$x_v(t) \geq 0, \; v = 1,...,V;$$

$$I_h(t) \geq 0, \; h = 1,...,V;$$

where $W_k^i(t)$ is the vector of the shadow value of capital for observation i, $i=1,...,N$. Taking into consideration that $W_k^i(t)$ is an endogenous variable, the Kuhn-Tucker conditions of (9) are[3]

$$w_v^i - \mathsf{m}_v^x \geq 0, \, x_v^* \geq 0, \, x_v^*(w_v^i - \mathsf{m}_v^x) = 0, \, v = 1,...,V;$$

$$-\sum_{m=1}^{M} \mathsf{m}_m^y y_m^j + \sum_{v=1}^{V} \mathsf{m}_v^x x_v^j - \sum_{h=1}^{H} \mathsf{m}_h^I (I_h^j - \mathsf{d}_h k_h^j) + \mathsf{m}_1^l - \mathsf{m}_2^l \geq 0,$$

$$\mathsf{l}^{j*} \geq 0, \, \mathsf{l}^{j*}(...) = 0, \, j = 1,...,N;$$

$$\sum_{j=1}^{N} \mathsf{l}^{j*} y_m^j - y_m^i \geq 0, \, \mathsf{m}_m^y \geq 0, \, \mathsf{m}_m^y (\sum_{j=1}^{N} \mathsf{l}^{j*} y_m^j - y_m^i) = 0, \, m = 1,...,M;$$

(10) $$x_v^* - \sum_{j=1}^{N} \mathsf{l}^{j*} x_v^j \geq 0, \, \mathsf{m}_v^x \geq 0, \, \mathsf{m}_v^x (x_v^* - \sum_{j=1}^{N} \mathsf{l}^{j*} x_v^j) = 0, \, v = 1,...,V;$$

$$\sum_{j=1}^{N} \mathsf{l}^{j*}(I_h^j - \mathsf{d}_h k_h^j) \geq 0, \, \mathsf{m}_h^I \geq 0, \, \mathsf{m}_h^I \sum_{j=1}^{N} \mathsf{l}^{j*}(I_h^j - \mathsf{d}_h k_h^j) = 0, \, h = 1,...,H;$$

$$1 - \sum_{j=1}^{N} \mathsf{l}^{j*} \geq 0, \, \mathsf{m}_1^l \geq 0, \, \mathsf{m}_1^l (1 - \sum_{j=1}^{N} \mathsf{l}^{j*}) = 0;$$

$$\sum_{j=1}^{N} \mathsf{l}^{j*} - 1 \geq 0, \, \mathsf{m}_2^l \geq 0, \, \mathsf{m}_2^l (\sum_{j=1}^{N} \mathsf{l}^{j*} - 1) = 0;$$

where the dual variables m_m^y and m_v^x are the current value of the Langrangian multipliers associated with the constraint on the output m and the variable input v, respectively. The Langrangian multipliers associated with the constraints on the intensity vector are m_1^l and m_2^l. The dual variable m_h^I is the current value of the Langrangian multiplier associated with the constraint on the net investment of the quasi-fixed factor h. Using the Envelope Theorem, it can be shown that the negative value of the shadow value of capital $(-W_{kh})$ is equal to m_h^I, $h=1,...,H$.

The Kuhn-Tucker conditions in (10) can be stated in a LCP form. The Kuhn-Tucker conditions in (10) for DMU i can be stated as

(11)
$$\begin{aligned} s &= q + Mz, \\ z &\geq 0, \\ s &\geq 0, \\ z's &= 0, \end{aligned}$$

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[3] The time index is suppressed for the sake of clearer exposition.

where M is a square matrix of order ($2V+N+M+H+2$) and q is an ($2V+N+M+H+2$) vector. The vectors s and z are the vector of slack variables and the vector of primal and dual variables, respectively. Conditions (11) are the Kuhn-Tucker necessary optimality conditions associated with the dynamic cost minimization problem in (9). The LCP consists of finding vectors z and s satisfying (11). Although, there is no objective function to be optimised, the LCP can be stated as a quadratic programming problem:

$$(12) \qquad \min_{z} \left\{ Q(z) = q'z + z'Mz : \ q + M'z \geq 0, z \geq 0 \right\}.$$

The function $Q(z)$ is bounded from below on the feasible set $F = \left\{ z : q + M'z \geq 0, \ z \geq 0 \right\}$. If $F = \varnothing$, the LCP is not feasible. If $F \neq \varnothing$, then there exist two possible cases. Either $Q(z^*) = min \ Q(z) = 0, z^* \in F$, implying z^* is the solution of the LCP or $min \ Q(z) > 0$ implying the LCP is feasible but has no solution (Al-Khayyal, 1987, 1989; Cheng, 1984).

The solution obtained by solving (12) provides the optimal variable input and quasi-fixed factor vectors minimizing the dynamic cost function in (10), the value of the intertemporal cost function and the value of the underlying shadow values of the quasi-fixed factors.

Alternatively, the long-run shadow cost can be generated through the dual of problem (9). The dual problem of (9) is as follows:

$$(13) \qquad \begin{aligned} &\max_{m_m^y, m_v^x, m_h^I, m_1^1, m_2^1} \left\{ \sum_{m=1}^{M} m_m^y y_m^i + \sum_{h=1}^{H} c_h^i k_h^i - m_1^1 + m_2^1 \right\} \\ &s.t. \\ &\quad m_v^x - w_v^i \leq 0, \ v = 1,...,V; \\ &\quad \sum_{m=1}^{M} m_m^y y_m^j + \sum_{h=1}^{H} m_h^I (I_h^j - d_h k_h^j) - \sum_{v=1}^{V} m_v^x x_v^j - m_1^1 + m_2^1 \leq 0, \ j = 1,...,N. \end{aligned}$$

where all variables are defined as before.

The directional quasi-fixed input distance function representing the efficiency of quasi-fixed factors is given by

(14) $\vec{D}_{qi}(y(t), x(t)^*, I(t), k(t); 0, g_I) = \sup\left\{ q_q(t): (x(t)^*, I(t) + q_q g_I) \in V(y(t): k(t)) \right\}$,

with $\vec{D}_{qi}(y(t), x(t)^*, I(t), k(t); 0, g_I) \geq 0$ and $x(t)^*$ is obtained through problem (12) or (13). The directional vector g_I projects the gross investment vector $I(t)$ onto the boundary of $V(y(t): k(t))$ at $(I(t) + q_q(t) g_I)$, $g_I \in \Re_+^H$ and $g_I \neq 0_H$. Properties of $\vec{D}_{qi}(.)$ are not presented in this version of the paper. Some of those properties are: non-increasing in $y(t)$, non-decreasing in $k(t)$ and $x(t)$ and concave in $I(t)$.

The directional quasi-fixed input distance can be interpreted as the number of times the input bundle g_I is overused in $I(t)$. The directional vector must be chosen. In practice, the observed gross investment vector can be chosen; implying the observed gross investment bundle determines the direction of scaling.

Using DEA, the directional distance function for quasi-fixed factors can be generated for each observation as follows:

(15)

$$\overline{D_{qi}}(y^i(t), x(t)^*, I^i(t), k^i(t); 0, g_I) = \max_{q_q, I^j(t)} q_q(t)$$

$$s.t$$

$$y_m^i(t) \leq \sum_{j=1}^{N} I^j(t) y_m^j(t), \; m = 1, ..., M;$$

$$\sum_{j=1}^{N} I^j(t) x_v^j(t) \leq x_v^*(t), \; v = 1, ..., V;$$

$$I_h^i(t) + q_q g_I - d_h k^i(t) \leq \sum_{j=1}^{N} I^j(t)(I_h^j(t) - d_h k_h^j(t)), \; h = 1, ..., H;$$

$$\sum_{j=1}^{N} I^j(t) = 1; \; I^j(t) \geq 0, \; j = 1, ..., N$$

Cost efficiency of quasi-fixed factors can be expressed as

(16) $\quad OE_I(t) = \dfrac{W_k(t)'(I(t) - I^*(t))}{w(t)'g_x - W_k(t)'g_I}$

where $I(t)^*$ is the optimal gross investment vector obtained by solving (12) or (13). Equation in (16) can also be decomposed in the following way:

$$(17) \qquad OE_I = \frac{W_k{}'(I(t) - I(t)^*)}{w(t)' g_x - W_k{}' g_I} = \sum_{h=1}^{H} \frac{W_{k_h}(I_h(t) - I_h(t)^*)}{w(t)' g_x - W_k{}' g_I} = \sum_{h=1}^{H} OE_h$$

where OE_h is the economic efficiency of the quasi-fixed factor h, $h=1,...,H$. This decomposition allows identifying the quasi-fixed factors that are over-invested or under-invested. A quasi-fixed factor is over-invested (under-invested) if $OE_h > 0$ (<0), whereas a value of $OE_h = 0$ implies an optimal investment level.

3. Data

Data on specialised vegetables firms covering the period 1991-1995 are obtained from a stratified sample of Dutch glasshouse firms keeping accounts on behalf of the LEI accounting system. The panel is balanced such that each firm is in the sample over the full five-year sampling period. The data contain 426 observations on 89 firms.

One output and six inputs (energy, materials, services, structures, machinery and installations and labour) are distinguished. Output mainly consists of potplants, vegetables, fruits and flowers. Energy consists of gas, oil and electricity, as well as heat deliveries by electricity plants. Materials consist of seeds and planting materials, pesticides, fertilisers and other materials. Services are those provided by contract workers and from storage and delivery of outputs.

Quasi-fixed inputs are structures (buildings, glasshouses, land and paving) and machinery and installations. Capital in structures, machinery and installations is measured at constant 1985 prices and is valued in replacement costs[4]. Labour is a fixed input and is measured in quality-corrected man years, including family as well as hired labour. Labour

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[4] The deflators for capital in structures and machinery and installations are calculated from the data supplied by the LEI accounting system. Comparison of the balance value in year t and the balance value in year t-1 gives the yearly price correction used by the LEI This price correction is used to construct a price index for capital and a price index for machinery and installations. These price indices are used as deflators.

is assumed to be a fixed input because a large share of total labour consists of family labour. Flexibility of hired labour is further restricted by the presence of permanent contracts and by the fact that hiring additional labour involves search costs for the firm operator. The quality correction of labour is performed by the LEI and is necessary to aggregate labour from able-bodied adults with labour supplied by young people (e.g., young family members) or partly disabled workers.

Tornqvist price indexes are calculated for output and the three composite variable inputs with prices obtained from the LEI/CBS. The price indexes vary over the years but not over the firms, implying differences in the composition of inputs and output or quality differences are reflected in the quantity (Cox and Wohlgenant, 1986). Implicit quantity indexes are generated as the ratio of value to the price index. A more detailed description of the data can be found in Table 1.

Table 1: Variables and Descriptive Statistics

Variable	Dimension	Mean	Standard Deviation
Output	1000 Guilders	1092.98	780.97
Energy	1000 Guilders	168.42	136.49
Materials	1000 Guilders	146.32	112.09
Services	1000 Guilders	94.73	60.11
Structures	1000 Guilders	969.66	755.12
Machinery and Installations	1000 Guilders	305.09	290.06
Labor	Man years	6.81	4.18

4. Empirical Results

Efficiency scores are generated for each horticulture firm in each year over the 1991-95 period using the program GAMS.[5] Results of overall short run efficiency and its decomposition are reported in Table 2. The short-run efficiency results indicate that horticulture firms over the period 1991-1995 have an average overall efficiency of

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[5] Due to space limitations, efficiency levels are not reported for each firm. The efficiency scores by firm are available from the authors upon request.

0.600. This implies that horticultural firms can save 40% on their variable costs by improving their technical and allocative performance. The decomposition of overall efficiency shows that, allocative efficiency is larger than technical efficiency, i.e. the average technical efficiency score for the period 1991-95 is 0.714 and the allocative efficiency score is on average 0.886. Results in Table 2 also show that the technical performance ranges between 0.669 (1994) and 0.783 (1995). Variation in allocative efficiency is smaller as it ranges between 0.859 (1991) and 0.903 (1994).

Table 2 Technical, Allocative and Cost Efficiency of Variable Inputs

Period	TE	AE	OE
1991	0.713	0.859	0.572
1992	0.677	0.896	0.573
1993	0.723	0.876	0.599
1994	0.669	0.903	0.571
1995	0.783	0.897	0.680
1991-1995	0.714	0.886	0.600

Table 3 presents the results of the inefficiency decomposition of different variable inputs by year. Results suggest overuse of all variable inputs except for materials in 1995. Furthermore, results show that the average overall inefficiency is much higher for energy rather than for materials and services. On average, in the period 1991-1995, energy comprises 29.5% of the overall inefficiency of 40% (see table 2). The contribution of materials is smallest, i.e. 3.3% of the overall inefficiency of 40% in the period 1991-1995 is coming from materials.

Table 3 Overall inefficiency by variable input

Period	Energy	Materials	Services
1991	0.325	0.044	0.059
1992	0.298	0.060	0.070
1993	0.300	0.044	0.068
1994	0.297	0.004	0.092
1995	0.258	-0.011	0.073

1991-1995	0.295	0.033	0.072

Table 4 presents the average long-term overall efficiency and its decomposition in the period 1991-1995. Long-term overall efficiency of all factors is, on average 9% smaller than short-term overall efficiency of variable inputs. Comparison of results in Table 4 with results in Table 2 shows that long-term and short-term efficiency have a similar size. However, allocative efficiency is smaller (by approximately 9%) in the long term rather than in the short term. These results suggest that the technical efficiency of variable factors of production does not substantially differ from technical efficiency of quasi-fixed factors of production. However, the allocation of quasi-fixed factors of production is less optimal than the allocation of variable factors of production. This may be explained by sluggish adjustment of quasi-fixed factors to long-term optimal levels due to the presence of adjustment costs.

Table 4 Long-term technical, Allocative and Cost Efficiency of All Factors of Production

Period	TE	AE	OE
1991	0.723	0.797	0.519
1992	0.688	0.806	0.494
1993	0.729	0.785	0.514
1994	0.671	0.824	0.495
1995	0.785	0.765	0.550
1991-1995	0.720	0.795	0.515

Table 5 provides further insight in the overall inefficiency of individual quasi-fixed factors. Results show that the firms in the sample are, on average over-invested in Machinery and installations, whereas the Structures is at the optimal level. The value of −0.003 for machinery/installations in 1991 suggests a situation of a slight under-investment in 1991, which is followed by over-investment in the years thereafter. The over-investment in machinery/installations may imply that firms are overall too eager to invest in new energy installations to reap the benefits of new, energy saving technologies.

Table 5 Overall inefficiency by quasi-fixed input

Period	Structures	Machinery/installations
1991	0.000	-0.003
1992	0.002	0.008
1993	-0.001	0.021
1994	0.000	0.033
1995	-0.000	0.038
1991-1995	0.000	0.019

5. Conclusions

This paper proposes input-based dynamic efficiency measures using an adjustment-cost directional input distance function approach. Short-run efficiency reflects the relative efficiency in the use of variable inputs, whereas long-run measures evaluate the relative efficiency of variable and quasi-fixed production factors.

These measures are illustrated for a sample of Dutch glasshouse horticulture firms over the period 1991-1995. The results presented show that these firms can achieve substantial cost savings from a better technical and allocative performance, both in the long and short run. The technical efficiency of Dutch horticulture firms is lower than the allocative efficiency. Results also provide evidence for the presence of adjustment costs since the allocative efficiency of quasi-fixed factors is lower than the allocative efficiency of variable production factors. The decomposition of inefficiency for individual variable inputs suggests overuse of all variable inputs and particularly for energy.

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