Drivers of Dynamic Efficiency of Dutch Vegetables Producers

Alfons Oude Lansink[1],Elvira Silva and Spiro Stefanou

Abstract

This paper measures dynamic technical and allocative inefficiency of a sample of horticultural firms over the period 1997-1999. Dynamic technical inefficiency is measured using a directional distance function and assumes that firms face adjustment costs in adjusting capital. Allocative inefficiency is determined residually using the duality between the dynamic directional distance function and the long-term cost function. Results suggest that substantial long-term cost savings (44%) can be obtained. Technical inefficiency is the largest component of cost inefficiency allowing for an average improvement of 33%. The average allocative inefficiency is 0.10. A bootstrap method is used to regress allocative and technical inefficiency as well as the cost inefficiency of individual inputs on socio-economic variables. Modernity of structures has a negative impact on technical inefficiency. Modernity of machinery and installations has a significant impact on the inefficiency in the use of individual inputs. Location in the glasshouse district, family labour, operator's age and modernity of structures have significant impacts on the inefficiency of individual inputs.

Key words: dynamic efficiency, bootstrap, DEA, horticulture, technical efficiency, allocative efficiency

[1] Alfons Oude Lansink is a professor of Business Economics at Wageningen University. Elvira Silva is an associate professor of economics at the University of Porto and Spiro Stefanou is a professor of agricultural economics from Pennsylvania State University and Wageningen University.

1. Introduction

The economics literature counts numerous studies that analysed technical and allocative efficiency of a sample of firms. In the literature on nonparametric efficiency analysis, only very few authors have acknowledged the dynamic nature of several factors of production like labour and capital[2]. Doing so is essential when assessing the actual potential for improving the performance in the short and long run. Many past studies in the static context have used a two-stage approach, where overall technical or allocative efficiency is estimated in the first stage, and then the efficiency estimates are regressed on a set of explanatory (socio-economic) variables. Simar and Wilson (2007) have proposed a bootstrap method that yields consistent parameter estimates in the second stage regression, particularly since the efficiency estimates are left truncated and are correlated in a complicated way.

The focus of past studies on the explanation of overall technical and allocative efficiency ignores the potential heterogeneity in the efficiency of individual inputs. Heterogeneity may be substantial as demonstrated by Oude Lansink and Ondersteijn (1996) for a sample of Dutch glasshouse firms. Chambers et al. (1998), developed a directional distance function and show that its application allows for disaggregating overall cost inefficiency into the contributions of individual inputs. The directional distance function has been extended to the dynamic case by Silva and Oude Lansink (2010). Application of the two stage approach to explain cost inefficiency of individual inputs allows for a more in-depth assessment of the driving factors of dynamic inefficiency.

The objective of this paper is to empirically investigate the driving factors behind dynamic overall technical and allocative inefficiency and dynamic cost inefficiency of individual inputs. The empirical application focuses on panel data of Dutch vegetables producers over the period 1997-1999. A robust single bootstrap approach developed by Simar and Wilson (2007) is used to regress socio-economic variables on overall technical and allocative inefficiency and cost inefficiency of individual inputs.

The remainder of this paper is structured as follows. The next section elaborates the concept of dynamic technical and allocative inefficiency and shows how measures of cost inefficiency can be obtained for each input. This is followed by the specification of the

[2] 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) develop dynamic efficiency measures using 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 (2007) propose lower and upper bounds on input-based dynamic measures of technical, allocative and cost efficiency.

empirical DEA models and the presentation of the data. Next, results are discussed and the paper concludes with comments.

2. Dynamic Efficiency Measurement

At any base period $t \in [0,+\infty)$, firms are assumed to minimize the discounted flow of costs over time:

$$
(1) \qquad
\begin{aligned}
W(y, K_t, w, c) = \min_{\{x(s), I(s)\}} \int_t^{\infty} e^{-r(s-t)} [w' x(s) + c' K(s)] ds \\
s.t. \\
\dot{K}(s) = I(s) - \delta K(s),\ K(t) = K_t \\
\vec{D}_i(y(s), K(s), x(s), I(s); g_x, g_I) \geq 0,\ s \in [t, +\infty).
\end{aligned}
$$

where $w \in \Re^N_{++}$ is a vector of rental prices of the variable input vector $x(s) \in \Re^N_{+}$ and $c \in \Re^F_{++}$ is a vector of rental prices of the capital stock vector $K(s) \in \Re^F_{++}$; $I(t) \in \Re^F_{+}$ is the vector of gross investments. The vectors *w* and *c* represent current market prices (i.e., at *s* = *t*) that the firm expects to persist indefinitely. This is the static expectations hypothesis. The dynamic directional distance function ($\vec{D}_i(\cdot)$)is defined as :

$$
\vec{D}_i(y(t), K(t), x(t), I(t); g_x, g_I) = \max\{\beta \in \Re : (x(t) - \beta g_x, I(t) + \beta g_I) \in V(y(t) : K(t))\},
$$

and is continuous, concave, increasing in *x*, decreasing in *I* and *y* and non-decreasing in *K*. Moreover, the dynamic directional distance function satisfies the translation property (Chambers, 1996; Silva and Oude Lansink, 2010).

The discount rate is $r > 0$ and the δ is a diagonal $F \times F$ matrix of depreciation rates. The firm is assumed to have the same discount rate and the same depreciation matrix in all base periods to discount future costs and depreciate the capital stocks. Given this assumption, *r* and δ can be suppressed as arguments of the optimal value function *W*(.).

Following Chambers (1996) and Silva and Oude Lansink (2010), overall inefficiency is defined as:

$$
(2) \qquad OE_i = \frac{w'x + c'K + W_K(.)'(I - \delta K) - rW(y, K, w, c)}{w' g_x - W_K(.)' g_I} = \vec{D}_i(y, K, x, I; g_x, g_I) + AE_i,
$$

with $AE_i \geq 0$. Note that dynamic cost inefficiency (and the dynamic directional input distance function) depends on the directional vector selected (g_x, g_I).

A directional distance function for dynamic factors can be derived as a special case of the dynamic directional input distance function:

$$\text{(3)} \qquad \vec{D}_{iI}(y, K, x, I; 0_N, g_I) = \max\{\beta_I : (x, I + \beta_I g_I) \in V(y : K)\},$$

with $g_x = 0_N$ and $\vec{D}_{iI}(y, K, x, I; 0_N, g_I) \geq 0$. Properties of $\vec{D}_{iI}(.)$ are derived from the properties of $\vec{D}_i(.)$ (e.g., strict concavity in *I*, increasing in *x*). The directional distance function in (3) provides a measure of technical inefficiency of dynamic factors of production.

The shadow cost inefficiency of dynamic factors can be expressed as

$$\text{(4)} \qquad OE_{iI} = \frac{W_K(.)'(I - I^*)}{-W_K(.)' g_I} = \vec{D}_{iI}(y, K, x^*, I; 0_N, g_I) + AE_{iI},$$

where $AE_{iI} \geq 0$ is the allocative inefficiency of dynamic factors. The shadow cost inefficiency of dynamic factors is the difference between the shadow value of actual gross investments and the shadow value of optimal gross investments, normalized by the shadow value of the direction vector g_I.

Equation in (4) can be further decomposed into the contributions of individual quasi-fixed factors of production.

$$\text{(5)} \qquad OE_{iI} = \frac{W_K(.)'(I - I^*)}{-W_K(.)' g_I} = \sum_{f=1}^{F} \frac{W_{K_f}(.)(I_f - I_f^*)}{-W_K(.)' g_I} = \sum_{f=1}^{F} OE_{iI_f},$$

where OE_{iI_f} is the shadow cost inefficiency of the f^{th} dynamic factor. This decomposition allows identifying the dynamic factors that are over-invested ($OE_{iI_f} < 0$) or under-invested ($OE_{iI_f} > 0$). The shadow cost inefficiency of the *F* dynamic factors can be all zero or all negative. However, OE_{iI_f} cannot be all positive due to the properties of the technology.

The directional variable input distance function is a particular case of the dynamic distance function and is given by

(6) $$\vec{D}_{ix}(y,K,x,I;g_x,0_F)=\max\left\{\beta_x:(x-\beta_x g_x,I)\in V(y:K)\right\}$$

with $g_I=0_F$ and $\vec{D}_{ix}(y,K,x,I;g_x,0_F)\geq 0$. The properties of $\vec{D}_{ix}(.)$ are inherited from the properties of the dynamic directional input distance function. Those properties are similar to the properties of the directional input distance function developed by Chambers, Chung and Färe (1996) including two additional properties: $\vec{D}_{ix}(.)$ is decreasing in *I* and nondecreasing in *K*.

Duality between $\vec{D}_{ix}(.)$ and the variable cost function $C(y,K,I,w)$ allows for expressing overall variable cost inefficiency as

(7) $$OE_{ix}=\frac{w'x-C(y,K,I,w)}{w'g_x}=\vec{D}_{ix}(y,K,x,I;g_x,0_F)+AE_{ix}$$

where $\vec{D}_{ix}(y,K,x,I;g_x,0_F)$ is the technical inefficiency measure of variable inputs and $AE_{ix}\geq 0$ is the allocative inefficiency of variable inputs. The cost inefficiency of variable inputs is the normalized difference between actual variable costs and minimum variable costs. The normalization is the market value of the direction vector g_x.

The cost inefficiency of variable inputs in (7) can be decomposed as follows:

(8) $$OE_{ix}=\frac{w'x-w'x^*}{w'g_x}=\frac{\sum_{n=1}^{N}w_n(x_n-x_n^*)}{w'g_x}=\sum_{n=1}^{N}OE_{ix_n}$$

where $C(y,K,I,w)=w'x^*$ and OE_{ix_n} is the cost inefficiency of the n^{th} variable input. The decomposition in (8) allows identifying variable inputs that are either overused ($OE_{ix_n}>0$) or underused ($OE_{ix_n}<0$). The cost inefficiency of the *N* inputs can be all zero or all positive. However, OE_{ix_n} cannot be all negative due to the properties of the technology.

3. Empirical Models

Consider a data series $\left\{\left(y^j, x^j, I^j, K^j, w^j, c^j\right); j = 1,..., J\right\}$ representing the observed behavior of each firm *j* at each time *t* and including information on *w* and *c* for each observation *j* at each time *t*. The dynamic directional input distance function measure of technical inefficiency for all factors of production can be generated for each observation *i* as follows:

$$
\vec{D}_i(y^i, K^i, x^i, I^i; g_x, g_I) = \max_{\beta^i, \gamma^j} \beta^i
$$

$$
\begin{aligned}
&s.t \\
&y_m^i \le \sum_{j=1}^{J} \gamma^j y_m^j, \quad m = 1,..., M; \\
&\sum_{j=1}^{J} \gamma^j x_n^j \le x_n^i - \beta^i g_{x_n}, \; n = 1,..., N; \\
&I_f^i + \beta^i g_{I_f} - \delta_f K_f^i \le \sum_{j=1}^{J} \gamma^j (I_f^j - \delta_f K_f^j), \; f = 1,..., F; \\
&\gamma^j \ge 0, \; j = 1,..., J.
\end{aligned} \tag{9}
$$

where γ is the $(J\times 1)$ intensity vector, J is the total number of firms in the sample. The direction vector adopted in the empirical application is $(g_x, g_I) = (x, I)$, i.e. the actual quantities of variable inputs and investments.

The flow version of the current value of the optimal value function for each observation is generated as:

$$
rW(y^i, K^i, w^i, c^i) = \min_{x, I, \gamma} \left[w^{i\prime} x + c^{i\prime} K^i + W_K^{i\prime} (I - \delta K^i) \right]
$$

$$
\begin{aligned}
&s.t \\
&\sum_{j=1}^{J} \gamma^j y_m^j \ge y_m^i, \quad m = 1,..., M; \\
&x_n \ge \sum_{j=1}^{J} \gamma^j x_n^j, \quad n = 1,..., N; \\
&\sum_{j=1}^{J} \gamma^j (I_f^j - \delta_f K_f^j) \ge I_f - \delta_f K_f^i, \quad f = 1,..., F; \\
&\gamma^j \ge 0, \; j = 1,..., J; \\
&x_n \ge 0, \; n = 1,..., N; \\
&I_f \ge 0, \; f = 1,..., F;
\end{aligned} \tag{10}
$$

where $W_K^i = W_K(y^i, K^i, w^i, c^i)$ is the vector of shadow values (or marginal cost of adjustment) of capital for observation *i*, *i=1,…,J*. The problem in (10) can be solved by expressing the Kuhn-Tucker conditions of (10) in a Linear Complementarity Problem form as in Silva and Stefanou (2007), or by solving the dual of problem (10) as in Silva and Oude Lansink (2010).

The solution to (10) provides the optimal variable input and dynamic factor vectors, the flow version of current value of the optimal value function and the value of the underlying shadow values of the quasi-fixed factors. Using these values, the dynamic cost inefficiency measure in (8) can be generated; the allocative inefficiency in (8) is calculated residually.

The technical inefficiency measure for *dynamic factors* in (8) can be generated for each observation as follows:

$$
\begin{aligned}
&\vec{D}_{iI}(y^i, K^i, x^{i*}, I^i; 0_N, g_I) = \max_{\beta_I^i, \gamma} \ \beta_I^i \\
&\quad s.t \\
&\quad y_m^i \le \sum_{j=1}^{J} \gamma^j y_m^j, \quad m = 1,\ldots,M; \\
(11) &\quad \sum_{j=1}^{J} \gamma^j x_n^j \le x_n^{i*}, \quad n = 1,\ldots,N; \\
&\quad I_f^i + \beta_I^i g_{I_f} - \delta_f K_f^i \le \sum_{j=1}^{J} \gamma^j (I_f^j - \delta_f K_f^j), \ f = 1,\ldots,F; \\
&\quad \gamma^j \ge 0, \ j = 1,\ldots,J.
\end{aligned}
$$

The directional vector is defined as $(g_x, g_I) = (0_N, I)$.

Given the technical inefficiency measure for the dynamic factors in (11), the shadow value of capital and the optimal level of the dynamic factors from solving (10), the allocative inefficiency measure can be calculated residually using (4). The shadow cost inefficiency of each dynamic factor can be computed using (10).

The technical inefficiency measure of *variable inputs* in (7) for observation *i* is generated as follows:

$$
\begin{aligned}
\vec{D}_{ix}(y^i, K^i, x^i, I^{i*}; g_x, 0_F) = \max_{\beta_x, \gamma\lambda^j} \ & \beta_x^i \\
s.t \quad & \\
& y_m^i \le \sum_{j=1}^{J} \gamma^j y_m^j, \quad m = 1,..., M; \\
& \sum_{j=1}^{J} \gamma^j x_n^j \le x_n^i - \beta_x^i g_{x_n}, \ n = 1,..., N; \\
& I_f^{i*} - \delta_f K_f^i \le \sum_{j=1}^{J} \gamma^j (I_f^j - \delta_f K_f^j), \quad f = 1,..., F; \\
& \gamma^j \ge 0, \ j = 1,..., J,
\end{aligned} \tag{12}
$$

where $I^i = I^{i*}$. The optimal level of dynamic factors for each observation is obtained from solving (10). The direction vector adopted is $(g_x, g_I) = (x, 0_F)$.

The minimum variable cost for each firm can be generated as

$$
\begin{aligned}
C(y^i, K^i, I^{i*}, w^i) = \min_{x,\gamma} \ & w^{i\prime} x \\
s.t \quad & \\
& \sum_{j=1}^{J} \gamma^j y_m^j \ge y_m^i, \quad m = 1,..., M; \\
& x_n \ge \sum_{j=1}^{J} \gamma^j x_n^j, \quad n = 1,..., N; \\
& \sum_{j=1}^{J} \gamma^j (I_f^j - \delta_f K_f^j) \ge I_f^{i*} - \delta_f K_f^i, \quad f = 1,..., F; \\
& \gamma^j \ge 0, \ j = 1,..., J
\end{aligned} \tag{13}
$$

The cost inefficiency of each variable input can be calculated using (8).

4. Data

Panel data on specialised vegetables firms covering the period 1997-1999 are obtained from a stratified sample of Dutch glasshouse firms keeping accounts on behalf of the LEI accounting system. The data set contains 265 observations on 103 firms, so the panel is unbalanced.

One output and six inputs (energy, materials, services, structures, installations and labour) are distinguished. Output mainly consists of vegetables, potted plants, 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 installations. Capital in structures and installations is measured at constant 1991 prices and is valued in replacement costs[1]. Labour is a fixed input and is measured in quality-corrected man-years, including family as well as hired labour. Labour 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, variable inputs and quasi-fixed 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.

Dynamic technical and allocative inefficiency and cost inefficiency for individual inputs are regressed in a second stage on socio economic variables. The variables reflect characteristics of the firm (modernity machinery and structures, share of family labor, size) and firm operators (age) and environmental conditions (location in the glasshouse district which is a region characterised by an extremely high density of glasshouses). Descriptive statistics of the socio-economic variables are also found in Table 1.

Table 1: Variables and Descriptive Statistics

Variable	Dimension	Mean	Standard Deviation
Quantities			
Output	1000 Guilders	1124.20	984.60
Energy	1000 Guilders	132.79	121.99
Materials	1000 Guilders	124.82	99.91
Services	1000 Guilders	85.59	73.56
Structures	1000 Guilders	833.38	697.18
Installations	1000 Guilders	229.39	243.31
Labor	Man years	6.62	5.17
Investments Structures	1000 Guilders	46.70	156.43
Investments Installations	1000 Guilders	41.34	128.90
Prices			
Energy	1991=1	1.14	0.03
Materials	1991=1	1.05	0.02
Services	1991=1	0.94	0.02
Structures	1991=1	1.51	0.13
Installations	1991=1	1.08	0.03
Socio-economic variables			
Glasshouse district	=1 for glasshouse district	0,57	0,50
Family Labour	Share family labour	0,50	0,25
Age Operator	years	46,14	10,38
Modernity Structures	book value/new value	0,56	0,21
Modernity Machinery	book value/new value	0,23	0,14
Size	Standardised firm units	0,67	0,53

5. Results

Inefficiency scores are generated for each horticulture firm in each year over the 1997-1999 period.[2] Table 2 reports average values of technical, allocative and cost inefficiency of variable and dynamic factors of production for each year and for the whole time period.

Table 2 shows that the average cost inefficiency over the 1997-1999 period is 0.44 implying that substantial cost savings (44%) can be obtained. Technical inefficiency is the largest component of cost inefficiency for each year and for the whole time period, allowing for an improvement between 39% (1997) and 26% (1999). The average allocative inefficiency of 0.10 suggests that Dutch vegetables firms can reduce costs by 10% through a better mix of variable and dynamic factors in the light of prevailing prices.

Table 2: Technical, Allocative and Cost Inefficiency of All Factors of Production

Period	TE	AE	OE
1997	0.39	0.09	0.48
1998	0.34	0.11	0.45
1999	0.26	0.13	0.39
1997-1999	0.33	0.10	0.44

Table 3 presents measures of cost inefficiency for each variable and dynamic factor input separately. The results in Table 3 suggest there is, on average, overuse of all variable inputs in the whole period 1997-1999. Overuse for energy and materials is particularly high as costs of energy and materials could be reduced, on average, by 32% and 26%, respectively. Cost inefficiency is lowest for services; for 1999 there is a small underuse rather than overuse of this variable input. The relatively large cost inefficiency for energy may be due to the fact that firms use a large variety of heating technologies. A group of firms uses more advanced and efficient technologies such as co-generators, heat storage and heat delivery by electricity plants, whereas a majority of firms still uses traditional heating technologies based on a combustion heater (Oude Lansink and Silva 2003). The results on the cost inefficiency of dynamic factors of production suggest that firms neither over-invest nor under-invest in structures and installations in 1997 and 1998. For the year 1999, the values of -0.40 and -0.02 indicate a large overinvestment in structures and a small overinvestment in installations. Inspection of the data reveals that average investments in structures and installations are indeed much higher in 1999 than in the two preceding years.[3] Therefore, firms have substantially increased their investment level in 1999 compared to the previous years. However, they have been over-investing in both structures and installations.

Table 3: Cost Inefficiency of Variable and Dynamic Factors of Production

Period	1997	1998	1999	1997-1999
Energy	0.33	0.33	0.31	0.32
Materials	0.26	0.25	0.27	0.26
Services	0.07	0.03	-0.02	0.03
Structures	0.01	-0.00	-0.40	-0.12
Installations	0.01	0.00	-0.02	-0.00

Variation in dynamic technical and allocative inefficiency are regressed on several exogenous variables capturing the effects of household and demographic characteristics, location and investment in physical capital (Table 4). Technical and allocative inefficiency are left truncated and are correlated between observations in a complicated way. A single bootstrap method (Simar and Wilson, 2007) has been adopted to obtain consistent parameter estimates. Two of the seven parameters are found to be statistically significant at the critical 5% level in the technical inefficiency and the allocative inefficiency regression. Modernity of structure significantly reduces technical inefficiency which suggests that firms can improve their technical performance by investing in the construction of glasshouses. Examples of such new glasshouse technologies are energy screens and heat storage. Size significantly increases allocative inefficiency, which suggests that large firms are less successful in achieving an optimal allocation of variable and dynamic factor inputs at given prices.

Table 4: Results of second stage regression technical and allocative inefficiency

Variable	Mean	Std. Err.	95% Conf. Interval	
Technical Inefficiency				
Intercept	0,570*	0,049	0,494	0,653
Glasshouse district	-0,006	0,018	-0,034	0,024
Family Labour	-0,002	0,046	-0,080	0,075
Age Operator	-0,001	0,001	-0,002	0,001
Modernity Structure	-0,279*	0,057	-0,376	-0,190
Modernity Machinery	-0,037	0,079	-0,165	0,098
Size	-0,005	0,022	-0,040	0,031
Allocative Inefficiency				
Intercept	0,043*	0,086	0,106	0,182
Glasshouse district	0,015	0,030	-0,035	0,063
Family Labour	0,086	0,079	-0,041	0,218
Age Operator	-0,002	0,002	-0,004	0,001
Modernity Structures	-0,112	0,082	-0,254	0,005
Modernity Machinery	-0,172	0,132	-0,402	0,039
Size	0,131*	0,038	0,072	0,195

*) Significant at 5%

Results in Table 5 provide more detailed insights into the drivers of dynamic inefficiency of individual inputs. Socio-economic factors of Table 4 have been regressed on variation in cost inefficiency of individual variable and dynamic factor inputs. Ordinary Least Squares is appropriate here since cost inefficiency is not truncated, i.e. it can take positive and negative values. The goodness of fit of the regression on structures, and to a lesser extent materials are much higher than the goodness of fit of the others. Also, particularly the structures equation outperforms the others in terms of the number of significant parameters: five out of seven parameters are significant at the critical 5% level. Structures are a major cost item and the results suggest that their cost inefficiency are well explained by the selected socio-economic variables.

Location in the glasshouse district increases cost inefficiency of structures and services, suggesting that firms located in the glasshouse district are less technically and allocatively efficient in using these inputs. Firms in the glasshouse district tend to overuse these inputs, which may be a result of better access to or higher costs of these inputs in this region.

The share of family labour in total labor decreases the cost inefficiency implying that firms that are predominantly operated by family labour are more inclined towards minimizing costs of energy and services.

Age of the firm operator increases cost inefficiency of structures and decreases cost inefficiency of energy. These results suggest that older firm operators are more successful in reducing costs of energy, possibly resulting in underuse. Higher cost inefficiency for older firm operators suggests that older operators are less technically and/or allocatively efficient in using structures.

Modernity of structures has a very significant negative impact on the cost inefficiency of structures. This result suggests that investing in new technologies improves the allocative and/or technical efficiency of the use of structures. Investments offer an opportunity to firm operators to bring the quantity of capital invested in structures in line with its long-term efficient quantity (allocative efficiency) and to improve the technical performance characteristics of the glasshouse (improving technical efficiency).

Modernity of machinery decreases cost inefficiency of machinery, a result that can be explained along the same lines as the impact of modernity of structures on cost inefficiency of structures. Interestingly, modernity of machinery also decreases the cost inefficiency of structures and energy. These results suggest structures and energy are used more efficiently if the technology of machinery is improved. Most likely this effect is caused by the fact that machinery and equipment predominantly consists of heating installations. Clearly new heating systems decrease the cost ineffiency of energy; they may also decrease the inefficiency of structures, particularly where it concerns the energy saving part of structures (e.g. energy screens).

Table 5: Second stage regression of cost inefficiency of dynamic and variable inputs

	Coefficient	Std, Err,	t
Structures (R^2=0,59)			
Intercept	0,844**	0,449	1,880
Glasshouse district	0,733*	0,160	4,590
Family Labour	0,635	0,428	1,480
Age Operator	0,017*	0,008	2,060
Modernity Structure	-7,177*	0,380	-18,900
Modernity Machinery	5,696*	0,678	8,400
Size	0,296	0,200	1,480
Machinery (R^2=0,04)			
Intercept	-0,137**	0,074	-1,840
Glasshouse district	0,010	0,026	0,370
Family Labour	0,069	0,071	0,970
Age Operator	0,001	0,001	0,920
Modernity Structure	-0,052	0,063	-0,820
Modernity Machinery	0,316*	0,112	2,820
Size	-0,012	0,033	-0,360
Energy (R^2=0,05)			
Intercept	0,493*	0,045	10,900
Glasshouse district	-0,020	0,016	-1,210
Family Labour	-0,146*	0,043	-3,390
Age Operator	-0,002**	0,001	-1,860
Modernity Structure	-0,012	0,038	-0,320
Modernity Machinery	-0,187*	0,068	-2,740
Size	0,055*	0,020	2,730
Materials (R^2=0,23)			
Intercept	0,241*	0,035	6,810
Glasshouse district	0,013	0,013	1,030
Family Labour	0,001	0,034	0,040
Age Operator	0,000	0,001	-0,180
Modernity Structure	0,005	0,030	0,160
Modernity Machinery	0,162*	0,053	3,030
Size	-0,043*	0,016	-2,720
Services (R^2=0,09)			
Intercept	-0,024	0,034	-0,690
Glasshouse district	0,023**	0,012	1,850
Family Labour	0,132*	0,033	4,030
Age Operator	0,000	0,001	-0,110
Modernity Structure	0,000	0,029	-0,010
Modernity Machinery	0,032	0,052	0,620
Size	-0,043*	0,015	-2,830

Conclusions

This paper measures dynamic technical and allocative inefficiency of a sample of horticultural firms over the period 1997-1999. Dynamic technical inefficiency is measured using a directional distance function; cost inefficiency is estimated using a dynamic cost function, assuming that firms face adjustment costs in adjusting capital. Cost inefficiency is decomposed into the contributions of variable and dynamic factors of production.

Results suggest that substantial long-term cost savings (44%) can be obtained. Technical inefficiency is the largest component of cost inefficiency suggesting that firms can reduce costs by 33% through improvements of dynamic technical inefficiency. The average dynamic allocative inefficiency is 0.10.

A bootstrap method is used to regress dynamic allocative and technical inefficiency, and cost inefficiency of individual dynamic and variable inputs on socio-economic variables. Modernity of structures has a negative impact on the overall technical inefficiency. Modernity of machinery and installations has a significant impact on the inefficiency in the use of individual inputs. Location in the glasshouse district, the share of family labour in total labor, age of the firm operator and modernity of structures have significant impacts on the efficiency of individual variable and dynamic factor inputs.

References

Caputo, M. R. 2005. *Foundations of Dynamic Economic Analysis: Optimal Control Theory and Applications*. Cambridge University Press.

Chambers, R. G., Y. Chung, and R. Färe. 1996. “Benefit and Distance Functions.” *Journal of Economic Theory* 70:407-419.

Chambers, R. G., Y. Chung, and R. Färe 1998. “Profit, Directional Distance Functions, and Nerlovian Efficiency.” *Journal of Optimization Theory and Applications* 98:351-364.

Chavas, J.-P., and T. Cox. 1999. “A Generalised Distance Function and the Analysis of Production Efficiency.” *Southern Economic Journal* 66: 294-318.

Cox, T. L., and M. K. Wohlgenant. 1986. “Prices and Quality Effects in Cross-sectional Demand Analysis.” *American Journal of Agricultural Economics* 68:908-919.

Färe, R., and S. Grosskopf 2000b. “Theory and Application of Directional Distance Functions.” *Journal of Productivity Analysis* 13:93-103.

Färe, R., and D. Primont. 2006. “Directional Duality Theory.” *Economic Theory* 29: 239-247.

Oude Lansink, A., and E. Silva. 2003. “CO2 and Energy Efficiency of Different Heating Technologies in the Dutch Glasshouse Industry.” *Environmental and Resource Economics* 24:395-407.

Silva, E. and A. Oude Lansink (2010). Dynamic Efficiency Measurement: A Directional Distance Function Approach. Working paper.

Silva, E., and S. Stefanou. 2007. “Nonparametric Dynamic Efficiency Measurement: Theory and Application.” *American Journal of Agricultural Economics* 89:398-419.

Simar, L. and Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics 136, 31-64*.