Assessing Input-Specific Technical Inefficiency of Dutch Vegetable Farms

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Abstract

Becoming technically efficient as a farm is important as differences in technical efficiency across farms has been identified as one of the major factors explaining differences in farm survival and growth, and changes in farm industry structure. This study employs Data Envelopment Analysis (DEA) to compute input-specific technical inefficiency scores for energy, materials, pesticides and fertilizer. The analysis focuses on panel data for Dutch indoor and outdoor vegetable farms over the period 2006-2016. A bootstrap truncated regression model is used to determine statistical relationships between producer-specific characteristics and technical inefficiency scores for the specified inputs. The results indicate that Dutch vegetable farmers have considerable inefficiencies in the use of variable inputs with respect to the best practice technology. The results indicate that indoor farmers can reduce their inefficiency in energy by 14.1%, materials by 22.1%, pesticides by 23.5% and fertilizer by 22.6 % while producing the same level of output. Outdoor farmers on the other hand can reduce the cost of energy by 8.4%, materials by 4.9%, pesticides by 11% and fertilizer by 9.1%. The study identified significant statistical associations between producer-specific characteristics and the inefficiency of the separate inputs. For indoor growers, short-term debt, long-term debt, degree of specialization and subsidy had significant associations with inefficiency scores. For outdoor growers, age, long-term debt and degree of specialization were found to be significantly associated with technical inefficiency. Based on the results, policies could be directed in building the capacity of farmers to reduce inefficiency while paying attention to farm characteristics that are associated with technical inefficiencies.

Keywords: vegetable farmers, Data Envelopment Analysis, input-specific inefficiencies, variable inputs.

Chapter 1

INTRODUCTION

1.1 Background

Vegetables continue to be recognized as essential for food and nutrition security globally. Vegetables are mankind's most affordable sources of vitamins and minerals needed for growth and development (Schreinemachers et al., 2018).

Fruit and vegetables accounted for approximately 14% of the total value of the EU's agricultural production in 2018 (Rossi, 2019). Being the second largest exporter of food, the agricultural sector of the Netherlands plays a critical role in global food security. Within the European Union (EU), the Netherlands holds the fifth position in the production of vegetables and the tenth in the production of fruits (Government of the Netherlands, 2018). This makes the Netherlands one of the largest producers of agricultural products in the EU and the world at large. In 2017, vegetables (including fruits and potatoes) alone accounted for 13% of total Dutch agricultural exports (Government of the Netherlands, 2018).

The growing demand for food worldwide has attracted increasing attention towards improving agricultural production efficiency (Xu et al., 2018). Growing environmental and sustainability concerns have added to the reasons why agricultural producers must make efficient use of inputs such as fertilizers, pesticides, seeds and strive to be technically efficient in their production activities (Wageningen Economic Research, 2019).

Technical efficiency is defined as the ability of a decision-making-unit (DMU) to obtain maximal output from a given set of inputs or to use the minimum inputs required to produce a given set of outputs Farrell (1957). Although technical efficiency is not a holistic measure of farm performance, it is a relatively good measure of farm performance as it is directly influenced by the management decisions of the farm contrary to performance indicators such as return on assets (ROA) and return on equity (ROE) which are dependent on market forces (Zhengfei and Oude Lansink, 2006).

Efficiency analysis of farms has received significant attention in scientific literature. Striving to be technically efficient as a farm has become important as differences in technical efficiency across farms has been identified as one of the major factors explaining differences in farm survival and growth, and changes in farm industry structure (Mugera et al., 2011).

Additionally, efficient use of resources in agricultural production is important for farmers as they produce homogenous products in a perfectly competitive global market. Factors of production particularly land and labour for agricultural purposes are increasingly becoming scarce for farm operators as they compete with other non-agrarian sectors (Kay et al., 2016).

Efficient use of inputs improves the profitability of farmers by reducing cost of inputs and protecting outputs. For example, pesticides improve the shelf life of produce, reduce fuel use for weeding and control invasive species (Skevas et al., 2012). Fostering efficient use of inputs also helps to reduce the negative impacts of pesticides on the environment, conserve biodiversity and protect beneficial organisms (Skevas et al., 2014). Producers who make efficient use of inputs do not reduce the stress of some input on the environment but also benefit directly by standing a higher chance of staying in business as they generate higher incomes relative to the inputs used.

As technical efficiency is directly linked to the decisions of farm managers, it is worth investigating farm characteristics that might have significant associations with technical efficiency. Many researches have explained differences in technical inefficiency scores by farm characteristics such as age, years of farm managerial experience, received subsidies and capital structure (Guesmi and Serra, 2015; Wilson et al., 2001; Adhikari and Bjorndal, 2012; Picazo-Tadeo et al., 2011). Exploring sources of inefficiency in relation to specific inputs is important to both public and private organizations that aim to improve performance of agriculture. Additionally, identifying such determinants of technical inefficiencies in the Dutch vegetable production can serve as an example to other European countries and to other countries that have similar environmental and climatic factors.

1.2 Problem Statement

The horticulture sector comprising of greenhouse and open ground vegetables and flower production is the highest value sector in Dutch agriculture, followed by grassland-based livestock keeping (FAO, 2008). As the Netherlands continues to experience keen competition in the global export of vegetables particularly with Spain, it positions Dutch vegetables farmers in constant strive for innovation and efficiency in their production activities.

There is extensive research on the technical efficiency of agricultural productions systems (Skevas and Oude Lansink, 2014; Xu et al., 2018; Oude Lansink et al., 2002; Alvares and Arias, 2004; Gutiérrez et al., 2017; Mohd Suhaimi et., 2017), but input-specific technical inefficiency of the composite Dutch vegetable subsector comprising of both indoor and outdoor is yet to be explored. Although Oude Lansink and Silva (2003) studied the efficiency of CO_2 emissions and energy use for vegetable farms in the Netherlands, the study did not investigate differences between indoor and outdoor vegetable growers.

Other studies (Karunarathna, 2014; Rajendran et al., 2015; Iráizoz et al., 2003, Singbo et al., 2015) that focussed on vegetables studied overall technical efficiencies without references to specific inputs but rather equi-proportionate reduction of all input or increase in all outputs were recommended. This study contributes to the literature by providing detailed information concerning input-specific technical inefficiencies of Dutch outdoor and indoor vegetable firms with respect to their underlying production technologies. Estimating inefficiency scores for specific inputs provides further insight for producers and policy makers. By this, one can for instance observe the differences in fertilizer efficiency between indoor and field conditions, but also differences in pesticide or energy efficiency under these two growing conditions. Additionally, determining inefficiencies in the vegetable sector for both outdoor and indoor with emphasis on specific inputs will make meaningful application to farmers as some inputs can be fixed or uncontrollable, so it might not be possible for farmers to influence some inputs especially in the short run. Therefore, it is useful to know the inefficiency related to separate inputs.

1.3 Objectives

The study will be guided by the following objectives.

1. To measure the input-specific technical inefficiency of both specialist indoor and outdoor vegetable production in the Netherlands.
2. To identify farm characteristics which are associated with input-specific inefficiency scores of specialist indoor and outdoor vegetable farmers in the Netherlands.

1.4 Research Questions

1. Does the distribution of input-specific technical inefficiency differ under indoor and outdoor growing conditions?
2. Which farm characteristics are associated with input-specific technical inefficiency scores of vegetable producers in the Netherlands?

1.5 Thesis Outline

This study is organized into five chapters. Chapter one introduces the study. Chapter two will present the theoretical framework on the Data Envelopment Analysis (DEA) and will review relevant literature on efficiency in agricultural production. Chapter three presents the methodology employed in the study. Chapter four will present the results of the analysis followed by a discussion in chapter. Finally, chapter six provides the conclusions of the study as well as policy implications.

Chapter 2

CONCEPTUAL FRAMEWORK

2.1 Approaches to Technical Efficiency Measurement

To estimate technical efficiency, two paradigms are followed in the scientific literature: parametric estimation using Stochastic Frontier Analysis (SFA) and non-parametric methods called Data Envelopment Analysis (DEA) and Free disposal hull (FDH). The former approach originates from the work of Aigner et al. (1977) and Meeusen & van Den Broeck (1977) who build on the work of Farrell (1957). SFA requires a parametric specification of the production function and seems the obvious choice when estimating efficiency in agriculture because it accounts for the stochastic characteristics inherent in agricultural processes (Lansink et al., 2002). However, SFA has also some disadvantages. According to Reinhard et al. (2000), SFA can confound the effects of mis-specification of functional forms (of both the production technology and inefficiency) with inefficiency. In addition, a flexible form is susceptible to multicollinearity, and the estimated function might violate the underlying production economic theory (Reinhard et al., 2000). Furthermore, SFA makes explicit assumptions about the distribution of the inefficiency term which is seldom known in practice (Lansink et al., 2002).

Farrell (1957) first introduced the theoretical basics for measuring productive efficiency. Following that, Charnes et al. (1978) proposed DEA which is one of the non-parametric approaches that uses mathematical programming techniques to estimate the technical efficiency of comparable decision-making units (DMUs). The DEA is relatively flexible in that it can easily relate multiple inputs to multiple outputs while imposing no assumptions about the functional form of the production technology and efficiency distribution (Iráizoz et al., 2003). In addition, DEA models are constructed to adhere to the underlying production economic theory. This study argues that the advantages of imposing adherence to the production economic theory outweigh the benefits of measuring statistical noise. Therefore, this study deems it appropriate to use DEA for computing the input-specific technical inefficiency of vegetable growers in the Netherlands.

2.2 Measuring Input Specific Technical Inefficiency: Conceptual Framework

The measurement of input specific technical inefficiency is related to the concept of input sub-vector efficiency which was introduced by Färe et al, (1994). The input sub-vector efficiency measures the efficiency of a subset of inputs used in the production process rather than the vector of all inputs (Kapelko, 2018). Since its development, other studies that have used the concept of input sub-vector include (Chen et al. 2005; D'Haese et al. 2009; Oude Lansink et al., 2002).

Alternatives to measuring input-specific inefficiency is using the Multi-directional Efficiency Analysis (MEA) developed by Asmild et al. (2003) following the work of Bogetoft and Hougaard (1999). Unlike DEA, MEA selects benchmarks such that the input reductions or output expansions are proportional to the potential improvements on efficiency identified by considering the improvement potential in each input or output separately (Asmild and Matthews, 2012).

Another type of input specific inefficiency measurement is the Russell-type measure of inefficiency developed by Färe and Lovell (1978). The Russel-type measure minimizes the mean of the reductions in each input dimension. As input and output decisions are not separable at the farm level, a Russell-type measure is straightforward for measuring technical inefficiency with respect to inputs and output inefficiency. The Russell-type measure allows a nonproportional increase and reduction of the separate inputs of interest (Färe et al., 1994).

Depending on the researcher and the purpose of the study, measuring inefficiency can be output-oriented or input-oriented. The former measures the extent to which a firm can increase output, fixing the input vector, whereas the latter measures the potential of a firm to reduce input without changing the output vector. As rational decision makers operating in competitive markets, farmers try to maximize economic performance by producing the maximum feasible output with the minimum input requirements. Hence, a simultaneous expansion of outputs and contraction of inputs has to be considered. To achieve this, a directional distance function will be employed in this study. The directional distance function measures the amount that a given observation can be projected in the directions g_{x_o} and g_{y_o} until it reaches the frontier (Chambers et al. 1998). The input-specific distances provide measures of inefficiency for all farmers.

Consider for instance $i = (1, \ldots, N)$ decision making units (DMUs) which use F fixed inputs (x_i^f) and S variable inputs $x = (x_1, x_2 \ldots, x_s) \in \Re_+^S$ to produce a single output y $\in \Re_+$. A production technology can be fully characterized by the input requirement set

$$T(y) = \{(x, y): \quad x \text{ can produce } y, \text{ given } x^f\} \qquad (1)$$

The production technology T(y) can also be expressed non-parametrically as T(y) = $\{(x, x^f)$: $Y'\lambda \geq y_i, X'\lambda \leq x_i, X^{f\prime}\lambda \leq x_i^f, I'\lambda = 1, \lambda \geq 0\}$. Where Y is the (N × 1) vector of observed outputs. y_i is the observed output level of firm i. X is the (N $\times S$) matrix of observed variable inputs, x_i is the vector of variable inputs used by firm i. X^f is the matrix (N x F) of observed fixed inputs. x_i^f is the vector of fixed inputs used by firm i. λ is a (N × 1) vector of intensity variables (firm weights). The technology set is considered nonempty and convex. Under the production technology set, we assume outputs, fixed inputs and variable inputs are freely disposable (meaning their reduction is not costly) (Grosskopf, 2000). The general directional distance function that aims at reducing variable inputs while simultaneously expanding output is expressed as:

$D(y_i, x_i^v, x_i^f; g_y, g_x) = \text{Max}\ (\beta: (y_i, x_i^v) \in T$ (2)

In model (2), g_x and g_y, refer to the directional vectors associated with variable inputs and outputs, respectively β denotes technical inefficiency measuring the equal maximum contraction of all variable inputs and maximum expansion of all outputs.

However, with reference to free disposability of fixed inputs, a directional distance function can be formulated to disaggregate technical inefficiency into input-output specific scores for each firm *i* as follows:

$D_o^t(x_1, x_2, x^f, \text{y}: g_{x_1}, g_{x_2}, g_y) = \text{Max}_{\beta\lambda}, \{\beta_{x_1} + \beta_{x_2} + \beta_y\}:(x_1 - \beta_{x_1} g_{x_1}, x_2 - \beta_{x_2} g_{x_2}, y_1 + \beta_y g_y) \in \mathbf{T}\}$ (3)

The Russell type measure of inefficiency (3) above allows for non-proportional contractions in each input and output such that all slacks are removed. Figure 1 shows a direct measure of how far point A must be projected along the (g_{x_1}, g_{x_2}) direction to reach the frontier $\mathbf{T}$ at A′ **.** The inefficiency scores β_{x_1}, β_{x_2},and β_y are truncated at 0, where a value of 0 indicates no improvement potential on the variable in question when a firm is efficient in the direction g_{x_1} and g_{x_2}.

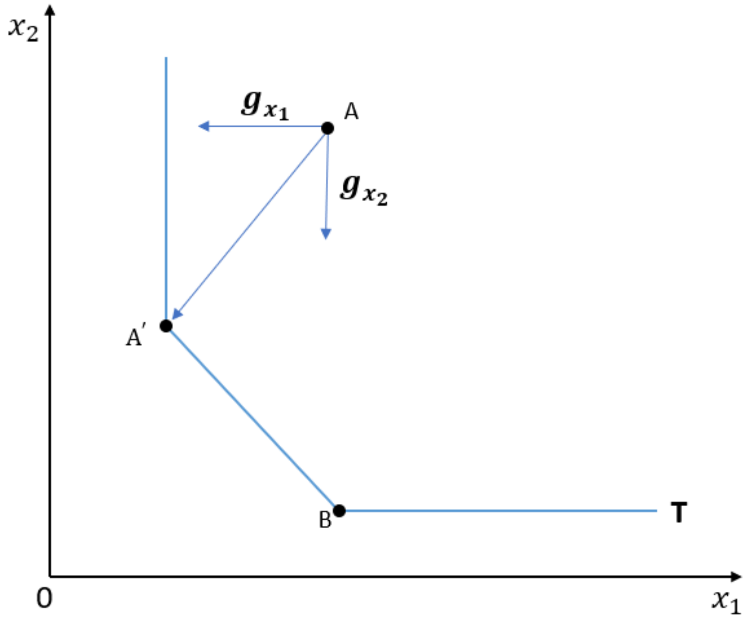

Figure 1. Russel type measure of efficiency (Skevas et al, 2012).

2.3 Factors that Explain Inefficiency

Identifying factors that tend to be associated with technical inefficiency of farms allows policy makers to target these factors when the aim is to improve the efficiency of the sector. These factors may consist of farm specific characteristics such as farmer's age, specialization, farmers experience measured in years, amount of government subsidy received, number of facilities and equipment (Mohd Suhaimi et., 2017). Depending on the purpose of the research, regional or environmental factors may also be considered in addition to farm specific characteristics to determine their relationship with inefficiency scores. An example includes Skevas et al. (2012) who explained output, undesirables and variable inputs inefficiency scores of Dutch arable farmers by environmental variables such as soil type, temperature, precipitation and biodiversity population. Although soil type and environmental factors cannot be influenced directly by farm managers, it is valuable to include these factors as control variables. This enables one to better understand the relationship between inefficiency scores and exogenous factors that affect them. It is essential to identify the sources of technical inefficiency in order to design private or public policies to improve performance (Lovell, 1995).

The effect of age on technical efficiency of farms has mixed conclusions in literature. In their study of factors that affect technical inefficiency of vegetables in Turkey, Bozoğlu and Ceyhan (2007) found older farmers to be more technically inefficient compared to younger farmers. This result is supported by the study by Mohd Suhaimi et. (2017) who indicated that older farmers are *ceteris paribus* more inefficient in Malaysia. This was attributed to that fact that younger farmers may be more willing to adopt new technologies and/or to have a stronger educational background. This is however contrary to the conclusion of Zhengfei and Oude Lansink (2006) who found that productivity growth of Dutch agriculture is positively related to older farmers. The implication was that older farmers had more experience. This experience gathered over the number of years in farming led to better managerial skills being acquired over the years. The studies of Guesmi and Serra (2015) and Ho and Illukpitiya (2014) also reported that age was statistically not significantly related with technical efficiency levels among farmers in Spain and Vietnam, respectively.

A farmer's level of education has been included in several studies to explain agricultural technical efficiency levels among farmers. Level of education usually spanned across a continuum starting from school leaving certificate, primary, secondary and university and specific professional training (type of agricultural instruction: non-specialized agricultural training, extension courses, professional degrees and university agricultural studies (Picazo-Tadeo et al., 2011). Adhikari and Bjorndal (2012) explained variations in the technical efficiency among a sample of Nepalese farmers. After computing efficiency scores using both SFA and DEA method, a second stage regression indicated positive relationship between technical efficiency and the level of farmer's education. Their study suggested that increasing investment in education may lead to better performance in the agricultural sector in Nepal. This finding confirms the study of Picazo-Tadeo et al., (2011) who found that efficiency levels among Spanish farmers who had secondary education were relatively lower that those with university education with 95% confidence level. Most studies have validated the hypothesis of Schultz (1964); that education increases the ability to perceive, interpret and respond to new events and enhances farmers' managerial skills, including efficient use of agricultural inputs. These results however contradict the findings of Zhengfei and Oude Lansink (2006) in the Netherlands whose results indicated that higher education failed to enhance productivity growth among Dutch arable farmers.

In the European Union and under the Common Agricultural policy (CAP), Latruffe et al. (2017) studied the association between agricultural subsidies and dairy farm technical efficiency. The researchers concluded that effect of subsidies on technical efficiency may be positive, null, or negative, depending on the country. Their analysis also revealed that the introduction of decoupling with the 2003 CAP reform weakens the effect that subsidies have on technical efficiency. This finding is also supported by the work of Ciaian and Swinnen (2009). More specifically, government subsidies have been found to have a significant negative impact on technical efficiency for German, Dutch, and Swedish crops farms (Zhu and Oude Lansink, 2010). This result was confirmed by Mohd Suhaimi et al., (2017) who indicated that increases in government subsidies increased technical inefficiency among Malaysian dairy farmers (Mohd Suhaimi et al., 2017). However, this is inconsistent with the findings of Guesmi and Serra (2015) for Spanish arable agriculture. Most of the studies asserted that while subsidies are expected to improve technical efficiency when they help farmers to invest in new technologies, they reduce farm performance when representing an income safety net.

Wilson et al., (2001) posit that wheat farmers with more farm managerial experience were less inefficient in Eastern England than those with fewer years of managing their farms. This finding is confirmed by Bozoğlu and Ceyhan (2007) and Zhengfei and Oude Lansink (2006) who also attribute higher efficiency levels to many years of managerial experience suggesting that when the farmer adjusts his goal in the later stage of the life cycle, they focus on improving efficiency (after investing and expansion). Farmers with many years of experience also make prudent decisions regarding farm expenditure (Mohd Suhaimi et al., 2017).

The concept of farm size has been defined differently by several people. Zhengfei and Oude Lansink (2006) defined farm size as the income generating capacity of all farm activities measured in standardized Dutch Farm Units. In their study, farm size was found to be insignificantly related to the productivity in Dutch arable agriculture. In Eastern England, Wilson et al., (2001) found larger farms (measured in terms of the land area cultivated) to be less inefficient. The authors attributed this result to the ability of larger farms to benefit from the economics of scales and discounts enjoyed from bulk purchases relative to smaller farms. The result conflict that of Bozoğlu and Ceyhan (2007) who establish that technical inefficiency is irrespective of farm size.

One unique characteristic feature of agricultural production is the long gestation period between planting and harvesting. Until crops are harvested, cost of inputs incurred during planting and growing creates negative cash flows (Bozoğlu and Ceyhan, 2007). This input-yield gap necessitates the need for farmers to access external funding. Constraints related to farmers' access to credit might have direct effects on farm performance. Mlote et al. (2013); Bozoğlu and Ceyhan, (2007) and Zavale et al. (2005) have all reported that access to credit by farmers was negatively related with inefficiency levels in Mozambique, Turkey and Tanzania respectively. For farmers in Australia, short-term debt was positively related to technical efficiency (Mugera and Nyambane, 2015) unlike in the Netherlands where it was insignificantly related (Zhengfei and Oude Lansink, 2006). This observation among Dutch arable farmers was explained by the fact that short-term debt is a routine decision associated with seasonal needs and liquidity of the farm. Long-term debt enhances productivity growth as it offers better investment opportunities for farmers and entrepreneurship. In a similar study, Lambert and Bayda (2005) explored the influence of debt structure on production efficiency of North Dakota crop farms in the USA. The study found that technical efficiency was positively related to intermediate debt farm as well as scale efficiency. However, short-term debt had a negative impact on technical efficiency.

Degree of specialization expresses the share of a single production activity in total production. It is expected that as a firm specializes in an activity it gets in-depth knowledge over time and thus improves efficiency in that activity (Zhu et al., 2012). Sometime the benefits of diversification may outweigh the benefits of focusing on a single activity as farmers may diversify to reduce risk especially for smallholder farmers (Coelli and Fleming, 2004). While specialization was found to improve technical efficiency for Spanish farmers (Guesmi and Serra, 2015), it was not significantly related to the technical efficiency of Benin vegetable farmers (Singbo, 2012).

Most farms are owned and controlled by families whose members provide an important source of labour for farm operations. Singbo (2012) showed that households that had a higher number of family members performed better in terms of technical efficiency in low land vegetable cultivation in Benin. In subsistence agriculture that relied mainly on family labour more family members contribute to having more labour on the farm. This result is in line with Zhengfei and Oude Lansink, (2006) who found that participation of family in Dutch agriculture increased productivity growth although the 5% impact was not statistically significant. In Turkey, Bozoğlu and Ceyhan, (2007) found family size to be insignificant. This was explained by underground factors such as off-farm income. The study revealed that smaller families without off-farm income were more efficient than the larger families having off-farm income. Binam et al. (2003) also add that, for crops that compete for family labour, a positive impact of family labour on the technical efficiency of one result in a decrease in the efficiency of the others.

The type of farm (i.e. organic or conventional) can be expected to have impact on technical efficiency (Mandau, 2007). As organic farming practices are deemed environmentally friendly and accepted by many governments around the world, questions concerning its capacity to contribute to food security continue to persist. Knowledge about input-specific productivity and efficiency differences between conventional and organic farms is important in designing policies to foster productive farming technologies that produce safe food, preserve land, and use energy efficiently (Lansink et al., 2002). Using data from olive-growing farms in Greece, Tzouvelekas et al. (2001) indicated that organic olive-growing farms exhibited a higher degree of technical efficiency (with reference to their production frontier) than do conventional olive-growing farms. This finding is contradicted by the study of Mayen et al. (2010) who studied productivity differences between organic and conventional dairy farms in the United States. Mayen et al. found that organic dairy farms where 13% less productive relative to conventional farms. This finding is consistent with that of Oude Lansink et al. (2002) who indicated that organic Finish crop and livestock farmers were less productive than their conventional counterpart. In the same study, it was however revealed that, organic farmers were more technically efficient than conventional farmers. For Dutch arable farms, Zhengfei and Oude Lansink (2006) found farm productivity to be insignificantly related to whether a farmer is an organic or conventional farmer.

Chapter 3

METHODOLOGY

3.1 Russel-Type Measure of Inefficiency for Specific Inputs

This research adopts a two-stage approach. First, DEA is employed to measure technical inefficiency for specific inputs used in the production of vegetables in the Netherlands. Second, a bootstrap truncated regression model is used to determine farm characteristics that are associated with technical inefficiency.

Consider for instance $j = (1, \ldots, N)$ decision making units (DMUs) which use F fixed inputs (x_j^f) and S variable inputs $x = (x_1, x_2 \ldots, x_s) \in \Re_+^S$ to produce a single output $y \in \Re_+$. Assuming strong disposability of fixed inputs, the Russell-type measure that decomposes technical inefficiency of the different variable inputs and the single output for each firm in the case of a directional distance function model (3) can be computed as the solution to the linear programming problem as:

$$\overrightarrow{D_0^t}(y_j,\ x_{1_j}, x_{2_j}, x_{3_j}, x_{4_j} : g_y, g_{x_1}, g_{x_2}, g_{x_3}, g_{x_4}) = \text{Max}\ \{(\beta_y + \beta x_1 + \beta x_2 + \beta x_3 + \beta x_4) \in T(y: x_j^f)\} \quad (4)$$

s.t.:

$$y_j + \beta_y g_y \leq \textstyle\sum_j^t \lambda Y \quad \text{(i)}$$

$$x_{1_j}^t - \beta_{x_1} g_{x_1} \geq \textstyle\sum_j^t \lambda X_1 \quad \text{(ii)}$$

$$x_{2_j}^t - \beta_{x_2} g_{x_2} \geq \textstyle\sum_j^t \lambda X_2 \quad \text{(iii)}$$

$$x_{3_j}^t - \beta_{x_3} g_{x_3} \geq \textstyle\sum_j^t \lambda X_3 \quad \text{(iv)}$$

$$x_{4_j}^t - \beta_{x_4} g_{x_4} \geq \textstyle\sum_j^t \lambda X_4 \quad \text{(v)}$$

$$x_j^f \geq \textstyle\sum_j^t \lambda x_j^f \quad \text{(vi)}$$

$$N1'\lambda = 1 \quad \text{(vii)}$$

$$\lambda \geq 0$$

$$0 < \beta \leq 1$$

Where Y is the (N × 1) vector of observed output. y_i is the observed output level of firm i. X refer to the (N × S) matrix of observed variable inputs, x_1, x_2, x_3 and x_4 are the vectors of specific variable inputs used by firm j. X^f is the matrix (N x F) of observed fixed inputs. x_i^f is the vector of fixed inputs used by firm j. λ is a (N × 1) vector of intensity variables (firm weights). β_{x_1}, β_{x_2} , β_{x_3} , β_{x_4} and β_y refer to the technical inefficiency with respect to specific variable inputs and output y respectively. Each computed value of β provides the maximum expansion of outputs and contraction of variable inputs if a firm has to operate efficiently given the directional vector ($g_y, g_{x_1}, g_{x_2}, g_{x_3}, g_{x_4}$) .The inefficiency scores (β) take values between 0 and 1, except for β_y (can be greater than 1) where a value of 0 indicates no improvement potential on the variable in question when a firm is efficient. The value of the firm weights identifies the firms that the relevant reference points for a given observation. The constraint $N1'$ λ = 1 (with $N1$ being an N × 1 vector of ones) implies the sum of the lambda's equals one and allows the sampled farmers to exhibit increasing, constant and decreasing return to scale (i.e. variable returns to scale (VRS)) technology. To approximate the technology under constant returns to scale (CRS), we omit the constraint $N1'$ λ = 1. To compute scale inefficiency, the difference between the VRS and CRS scores is computed.

3.2 Data and Variables

Data on specialised vegetable farms for the period 2006–2016 is obtained from Wageningen Economic Research (WeCR). WeCR uses stratified sampling for specialist indoor and outdoor Dutch vegetable farms which are collected for the European Farm Accounting Data Network (FADN). The panel is unbalanced and on average farms stay in the sample for 10-11 years for indoor growers and 6 years for outdoor growers. After removing farms with missing information. The dataset used for estimation comprises 1090 observations from 222 indoor farms and 218 observations from 63 outdoor farms. Table 1 below provides descriptive statistics of the variables in the dataset.

For outputs and inputs (except land and labour), the available sample data contain information about the revenues and expenses, respectively and no information about physical quantities. Real Price indices for the specific output, fixed and variables inputs were obtained from Eurostat to compute the implicit quantities. To obtain implicit values for the variables, monetary values were divided by their respective price/ Tornqvist indices.

One output and seven inputs (land, labour, capital, fertilizer, pesticide, energy and materials) are considered for both categories. Output consists of total revenue which was deflated with the price index for agricultural good output using 2010 as a base year. Total revenue comprises of mainly vegetables, other horticultural products, cut flowers and turnips. Fixed inputs include capital, land and labour while variable inputs include energy, pesticides, fertilizers and materials. Capital comprises closing balance sheet values for machinery, buildings, glasshouses and installations deflated to 2010 prices using a Tornqvist index (some outdoor farms have glasshouses and were included in the calculation of capital).

Table 1 **Descriptive statistics (Dutch vegetable farms 2006-2016)**

Variables	Dimension	Indoor Growers		Outdoor Growers	
		Mean	SD*	Mean	SD
Output	10000 Euros	180.00	266.74	92.12	131.26
Land	Hectares (ha)	6.84	7.68	44.07	52.08
Labour	10000 hours	2.70	3.60	2.24	3.48
Capital	10000 Euros	140.2	256.96	54.667	79.18
Fertilizers	10000 Euros	3.11	3.72	1.82	2.41
Pesticides	10000 Euros	2.16	2.92	2.94	4.46
Materials	10000 Euros	13.09	16.38	14.30	20.88
Energy	10000 Euros	47.46	69.25	2.54	3.82

* SD *means standard deviation*

Land represents the total farm size measured in hectares. Labour is calculated in terms of the number of hours worked per year and includes family as well as hired labour. Energy consists of gas, oil and electricity, as well as heat deliveries by electricity plants measured as production expenditures deflated to 2010 prices. Materials consist of expenditure on seeds and planting materials, insecticides, fungicides and other materials deflated to 2010 using a Tornqvist index based on their respective real price indices. Pesticides were measured as expenditures deflated to 2010 using the pesticide price index. Fertilizers were measured as expenditures deflated to 2010 prices using the fertilizer price index.

3.3 Second-Stage Truncated Bootstrap Regression

Non-parametrically estimated efficiency scores are serially correlated by construction (Simar and Wilson, 2007). Thus, the use of Ordinary Least Square approach would violate independence assumption required in regression analysis. To correct for this, (Simar and Wilson, 2007) developed the single and the double truncated bootstrap procedures. This study uses the single truncated bootstrap regression to estimate statistical associations of producer-specific characteristics and inefficiency scores. The adoption of the single truncated bootstrap regression permits valid statistical inference to be made in the second stage truncated regression (Simar and Wilson, 2007). The bootstrapping procedure can be described below and is similar to that of Skevas et al., (2012). Using DEA computed input-specific inefficiency scores, the conceptual single-bootstrap truncated regression model is defined as:

$$\beta_{ki} = \delta Z_i + \varepsilon_i \geq 0 \qquad i= 1\ldots\ldots n \qquad (5)$$

where β_{ki} is the estimated technical inefficiency score of input $\boldsymbol{k}$ of the i^{th} farm, Z_i is a vector of farm specific characteristics, δ_i its associated vector of coefficients, and ε *is* the error term. The distribution of the error term is assumed to be truncated normal, with zero mean, unknown variance, and left truncated at point 0- δZ_i (Simar and Wilson, 2007). The maximum likelihood method is used to obtain estimates $\hat{\delta}$ as well as an estimate $\widehat{\sigma_\varepsilon}$, where σ_ε is the standard deviation of the error term. Next, linear predictions of the inefficiency scores are generated based on the estimated coefficients and the producer-specific characteristics. For 2,000 iterations, errors are sampled out of a truncated distribution using the computed variance σ_ε. Succeeding, truncated regression models are computed for all iterations by regressing the producer-specific characteristics on the predicted inefficiency scores. Lastly, confidence intervals of the estimated coefficients are computed based on the empirical distribution to conclude on the statistical significance.

Producer-specific characteristics that may influence the technical inefficiency with respect to the specified inputs include production period in years, age, capital structure categorised into short- and long-term debt ratio. Short- and long-term debt are separated to investigate their differential influence on the input-specific technical inefficiencies. Table 2 below shows descriptive statistics of the producer-specific characteristics of interest. Age refers to the age of the oldest farm manager. Short- and long-term debt refers the ratio of short- and long-term debt to total assets. The Herfindahl-Hirschman Index (HHI) are computed as proxy for the farm specialization (Kim et al., 2012; Dimara, 2005). It is computed by summing the squared revenue shares of arable crops, vegetables, flowers, cut-flowers, turnips and other horticultural and other sources of revenue. HHI signifies a higher degree of specialization as it approaches 1. Likewise, a value closer to 0 signifies a more diversified vegetable crop production. For HHI indices of 0.76 and 0.66, indoor and outdoor farms are respectively considered to be specialized. Subsidy refers to the total subsidy received from the government. Period refers to the all the years under study. For outdoor growers, the period is treated as a dummy due to inadequate number of annual observations. All production period before and including 2013 designated as 0 and the period beyond as 1. 2013 serves as the break-point to allow even distribution of observations between the periods.

Table 2 **Descriptive statistics of producer- specific characteristics**

Variable	Dimension	Indoor		Outdoor	
		Mean	S.D.	Mean	S.D.
Age	10 years	4.90	0.85	5.01	0.84
Short-term debt ratio	-	0.118	0.676	0.146	0.216
Long-term debt ratio	-	0.477	0.657	0.432	0.322
HHI	-	0.76	0.186	0.66	0.21
Subsidies	10000 Euros	2.481	5.691	0.720	1.880
Period	0			2006 - 2013	
	1			2014 - 2006	

Chapter 4

EMPIRICAL RESULTS

4.1 Input-Specific Technical Inefficiencies

Technical inefficiency (TI) scores for one output and four variable inputs were computed using R software (version 3.6.1) after developing Linear Programming models following the directional distance functions in expression (4) above for each firm per year. Table 3 and 4 show annual averages under constant returns to scale (CRS) and variable returns to scale (VRS) for indoor and outdoor vegetable growers, respectively. Scale inefficiency for each input is presented in table 5. Scale inefficiencies were computed by taking the difference between mean TI scores under CRS and VRS for each input. For outdoor growers, TI scores were not computed for the years 2008 & 2010 due to inadequate number of observations. As the distributions for all inputs are positively skewed, the median values are also provided to give a better representation of central tendency than the mean.

Results from Table 3 & 4 show that for indoor growers, the average technical inefficiency scores over the period 2006 – 2016 are 0.000, 0.141, 0.221, 0.226 and 0.236 for output, energy, materials, pesticides and fertilizer respectively under the VRS assumption. Outdoor growers on the other hand have technical inefficiency scores of 0.000, 0.084, 0.049, 0.110 and 0.091 for output, energy, materials, pesticides and fertilizer respectively under the VRS assumption. A similar trend of inputs inefficiency scores can be observed for CRS for the two growing systems. Table 3&4 show that inputs inefficiencies are relatively higher for indoor growers than outdoor growers with respect to their separate production technologies. The degree of variation of inefficiency among the specific inputs across the two growing systems is quite different. Inefficiency scores are quite similar for the various inputs for indoor growers except for energy. Energy and materials have the lowest inefficiency score for indoor and outdoor growers respectively whereas pesticide is the most technically inefficient input in both growing systems. For indoor growers, the annual averages of TI scores under VRS ranges from 8.1 % to 26.2% for energy, 10.3% to 36.1% for materials, 15.1% to 32.8% for pesticide and 17.7% to 28.8% for fertilizer. For outdoor growers, TI scores ranges were 5.7 % to 12% for energy, 0.6% to 13.8 % for materials, 2.6 % to 17.7% for pesticide and 3.3% to 14.0% for fertilizer under VRS.

Table 3 Technical Inefficiencies for one output and four variable inputs for Dutch Indoor growers (2006-2016).

	CRS					VRS				
Period	Output	Energy	Materials	Pesticides	Fertilizer	Output	Energy	Materials	Pesticides	Fertilizer
2006	0.000	0.156	0.355	0.277	0.268	0.000	0.135	0.250	0.275	0.219
2007	0.000	0.186	0.361	0.416	0.321	0.000	0.147	0.283	0.299	0.269
2008	0.000	0.185	0.573	0.454	0.307	0.000	0.090	0.361	0.278	0.229
2009	0.000	0.327	0.193	0.236	0.430	0.000	0.181	0.148	0.151	0.287
2010	0.000	0.160	0.270	0.222	0.222	0.000	0.113	0.195	0.188	0.177
2011	0.000	0.121	0.282	0.221	0.329	0.000	0.098	0.237	0.181	0.288
2012	0.000	0.120	0.300	0.259	0.207	0.000	0.109	0.217	0.192	0.180
2013	0.000	0.313	0.272	0.366	0.212	0.000	0.225	0.235	0.328	0.197
2014	0.001	0.309	0.242	0.304	0.286	0.001	0.262	0.189	0.261	0.271
2015	0.000	0.150	0.115	0.288	0.299	0.000	0.106	0.103	0.213	0.206
2016	0.000	0.128	0.228	0.286	0.283	0.000	0.081	0.213	0.217	0.188
mean	**0.000**	**0.196**	**0.290**	**0.303**	**0.288**	**0.000**	**0.141**	**0.221**	**0.235**	**0.228**
median	**0.000**	**0.125**	**0.236**	**0.266**	**0.246**	**0.000**	**0.000**	**0.034**	**0.029**	**0.046**

Table 4.0 Technical Inefficiencies for one output and four variable inputs for Dutch Outdoor growers (2006-2016) *

	CRS					VRS				
Years	Output	Energy	Materials	Pesticides	Fertilizer	Output	Energy	Materials	Pesticides	Fertilizer
2006	0.000	0.129	0.123	0.263	0.136	0.000	0.089	0.082	0.152	0.033
2007	0.000	0.218	0.016	0.210	0.174	0.000	0.082	0.017	0.097	0.081
2009	0.000	0.147	0.016	0.218	0.184	0.000	0.057	0.015	0.026	0.061
2011	0.000	0.099	0.106	0.143	0.096	0.000	0.088	0.045	0.088	0.079
2012	0.000	0.187	0.062	0.176	0.168	0.000	0.071	0.006	0.060	0.074
2013	0.000	0.223	0.137	0.308	0.306	0.000	0.067	0.015	0.102	0.100
2014	0.000	0.223	0.182	0.297	0.289	0.000	0.114	0.076	0.160	0.140
2015	0.012	0.118	0.157	0.230	0.245	0.000	0.065	0.047	0.132	0.139
2016	0.000	0.172	0.218	0.255	0.177	0.000	0.120	0.138	0.177	0.115
mean	**0.001**	**0.168**	**0.113**	**0.233**	**0.197**	**0.000**	**0.084**	**0.049**	**0.110**	**0.091**
median	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**

* the study period does not include 2007 & 2010 for outdoor growers.

Table 3 **Scale inefficiencies for specific inputs**

Output/Input	Indoor	Outdoor
Output	0.000	0.000
Energy	0.055	0.085
Materials	0.069	0.064
Pesticides	0.068	0.123
Fertilizer	0.060	0.106

Figure 2 & 3 below show the respective distributions of mean TI scores for specific inputs under both production systems. It is observed that the distributions are positively skewed indicating that majority of the sampled vegetable growers have inefficiency scores of less than the mean values. The figures show that the patterns of TI scores are quite similar across the specified inputs but different across the two production systems. Figure 2 & 3 show that the most efficient vegetable growers under both production systems are observed to cluster between 0.0 - 0.2 inefficiency levels with respect to all inputs particularly for energy. This observation also indicates most of the farms in each group are close to their respective production frontiers. This is evidenced by the platykurtic (flatness) nature of the distributions especially for outdoor growers for technical inefficiency of 0.2 and beyond for all inputs.

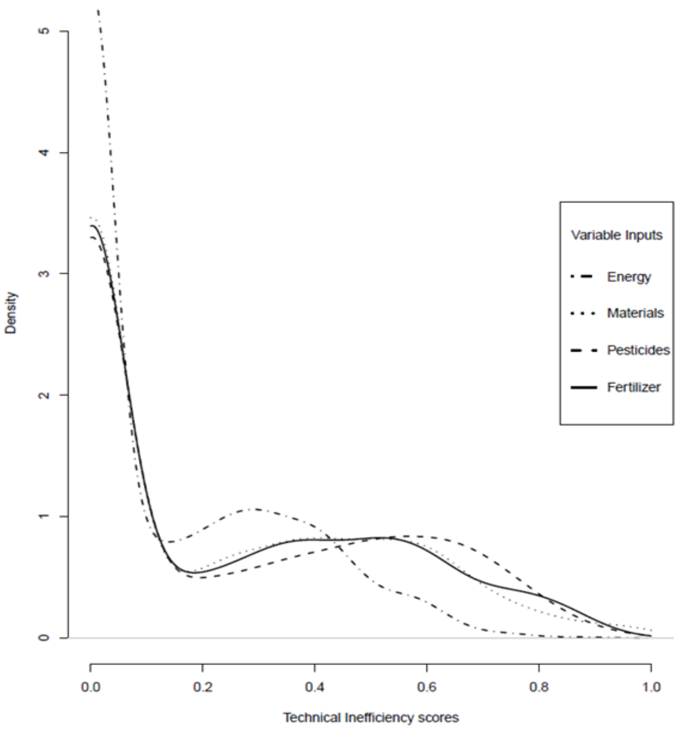

Figure 2. Kernel density plot of technical inefficiency scores for indoor growers (2006-2016)

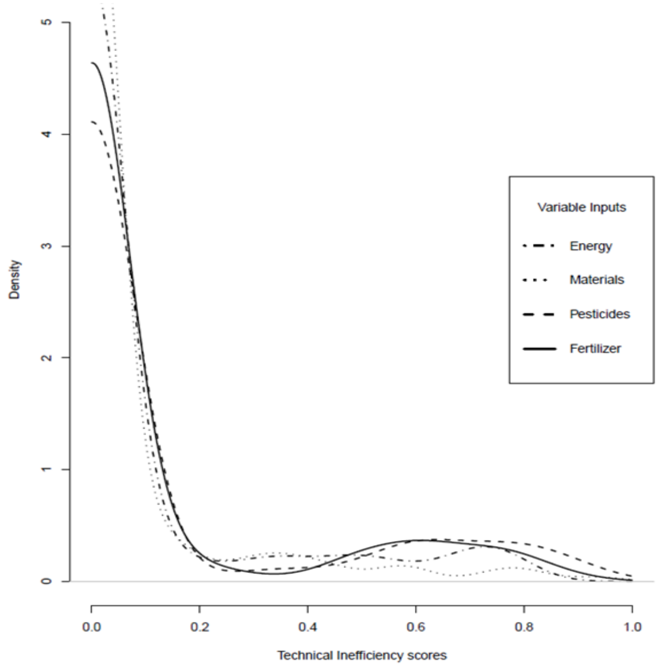

Figure 3**.** Kernel density plot of technical inefficiency scores for outdoor growers (2006-2016)

4.2 Determinants of Input-specific inefficiencies

The next stage involves the identification of producer-specific characteristics that are associated with the variation in technical inefficiencies of the specified variable inputs. Table 6 & 7 present the parameter estimates and the 10%, 5%, 1% significant levels. According to the truncated bootstrap regression model, four out of the five characteristics are significant for indoor growers whereas three were significant for outdoor growers. For each input, the parameter estimate gives an indication of the direction of the relation between the variables and the inefficiency interpreted by the value of their marginal effects. A negative parameter estimate indicates that the particular variable is associated with a reduction in inefficiency of the said input. The result provides detailed information on each producer-specific characteristic and how they are related to the technical inefficiency of each of the variable

Table 4 **Second stage results for determinants of inefficiency (Indoor Growers)**

Farm	**Energy**		**Material**		**Pesticide**		**Fertilizer**	
Characteristics	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Constant	0.2336	***	0.3396		0.4672	***	0.2720	***
2007	0.0191		0.0279		0.0324		0.1266	***
2008	-0.0494		0.2594	***	0.0484		0.1161	**
2009	0.1256	***	-0.1550	***	-0.1971	***	0.2364	***

2010	0.0459		0.0562		-0.0557		0.0885	*
2011	-0.0274		0.1200	***	-0.0285		0.3446	***
2012	-0.0019		-0.0374		-0.0877	*	0.0340	
2013	0.1341	***	-0.0664	*	0.0215		-0.0307	
2014	0.2222	***	-0.1511		-0.0081		0.1237	***
2015	-0.0003	***	-0.2781	***	0.0022		0.0963	**
2016	-0.0812	**	-0.0474		-0.0708		0.0042	
Age	0.0003		0.0018		-0.0008		0.0013	
SD_ratio	0.3099	***	0.3179	***	0.3358	***	0.3436	***
LD_ratio	-0.0880	***	-0.0691	***	-0.0390		-0.0952	***
HHI	-0.0911	*	0.2425	***	0.3606	***	0.3407	***
Subsidies	-1.4E-06	***	-6.7E-07	***	-9.0E-07	***	-1.6E-06	***
Marginal effects on Inefficiency								
Age	0.0001		0.0009		-0.0002		0.0006	
SD_ratio	0.1324	***	0.1305	***	0.1367	***	0.1413	***
LD_ratio	-0.0265	***	-0.0225	***	-0.0134		-0.0301	***
HHI	-0.0241	*	0.1551	***	0.2650	***	0.2523	***
Subsidies	-4.4E-07	***	-2.3E-07	***	-3.1E-07	***	-5.1E-07	***

*Confidence interval correspond to *=10%, **=5%, ***=1%. Note: All marginal effects were computed at the mean of the data.

Table 5 **Second stage results for determinants of inefficiency (Outdoor Growers)**

Farm	**Energy**		**Material**		**Pesticide**		**Fertilizer**	
Characteristics	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Constant	-0.3142		-0.9252	*	0.1229		0.0825	
2014-2016	-0.0467		0.3118		-0.1419	*	-0.0619	
Age	0.0118	**	0.0101		0.0088	*	0.0055	
SD_ratio	-0.4476		-0.1963		-0.1130		0.1994	
LD_ratio	0.3003	*	0.3675		0.2519	*	0.1660	
HHI	-0.4274		0.3645		-0.3894	*	-0.4062	
Subsidies	1.4E-06		-1.8E-06		-1.2E-06		8.2E-07	
Marginal effects on inefficiency								
Age	0.0011	**	0.0086		0.0077	*	0.0091	
SD_ratio	-0.1346		-0.0671		-0.039		0.0784	
LD_ratio	0.1560	*	0.1851		0.1219	*	0.0732	
HHI	-0.0692		0.2198		-0.0658	*	-0.0689	
Subsidies	5.6E-07		-6.6E-07		-4.3E-07		3.0E-07	

Chapter 5

DISCUSSION OF RESULTS

5.1 Input-Specific Technical Inefficiencies

The tables of results indicate that the Dutch vegetable farms have considerable technical inefficiency in the use of the specified variable inputs relative to output. It is also found that on average, the farms are not operating at their optimal sizes evidenced by their scale inefficiencies. The assumption of VRS is thus more justified. For both indoor and outdoor growers, the mean technical inefficiency scores of 0 for output means that farmers within the sample cannot expand output any further. For indoor growers, input-specific technical inefficiencies of 0.141, 0.221, 0.226 and 0.236 means that the sampled farmers can respectively reduce their technical inefficiency of energy by 14.1%, materials by 22.1%, pesticides by 22.6 % and fertilizer by 23.6 % while producing the same level of output under the VRS assumption. Table 4 shows that outdoor growers on the other hand with technical inefficiency scores of 0.084, 0.049, 0.110 and 0.091 can reduce the cost of energy by 8.4%, materials by 4.9%, pesticides by 11 % and fertilizer by 9.1 % respectively while producing the same output level with reference to the current technology.

These results suggest a considerable inefficiency in the use of variable inputs for Dutch vegetable growers. Differences in the inefficiency for the specific inputs can be attributed to difference in the way these inputs are managed and due to environmental factors for outdoor growers whose performance can be influenced by the weather. With reference to their production technology, this study considers inefficiencies in the use of variable inputs for the indoor growers to be high as production takes place under controlled environment hence statistical noise can be assumed to be minimal. These values of inefficiency suggest that there is significant scope to improve the utilization of the variable inputs. This is crucial for the farmers producing in such a competitive industry especially as they produce homogeneous products.

Although outdoor growers turn to have low input-specific inefficiencies in the use of input relative to indoor growers, one cannot be conclusive about this by directly comparing these two systems as they are different in terms of their underlying production technologies. However, there is noticeable differences in the distribution of inefficiency between the two systems as shown by Figures 2 & 3. For the separate inputs, indoor growers are bimodally distributed with majority of farmers clustering within 0.0-0.2 and 0.3-0.7 inefficiency intervals.

The distribution of outdoor grower is rather flat after 0.2 indicating variations in inefficiency among the farmers is relatively minimal for all inputs.

Among the variable inputs analysed, energy and materials are the most efficiently utilized resources for indoor and outdoor respectively whiles pesticide is the most technically inefficient input. Efficiency in the use of energy is particularly important as the greenhouse industry accounts for 79% of total energy use in Agriculture in the Netherlands (Aramyan et al, 2007). The relative low inefficiency in the use of energy may signal that farmers are motivated to improve the efficiency of energy use as profits are highly dependent on energy costs for indoor growers (Oude Lansink and Ondersteijn, 2006). Another factor could be the focus of policy makers to minimize energy use by the glasshouse industry. An example is the 1995 covenant between the Dutch glasshouse industry and the government requiring the former to improve its energy use efficiency by 65% by 2010 compared to the levels in 1980 (Aramyan et al., 2007). Other concerns such as reduction of CO2 emissions as required under the Kyoto protocol could be a motivating factor for the famers to improve the efficiency of energy usage. Golaszewski et al, (2012) posits that a more energy efficient agriculture will be increasingly demanded by food-chain partners and society and is also a necessity in view of competitiveness. The inefficiency of energy for indoor growers is supported by the findings of Oude Lansink and Silva (2003) who reported an inefficiency of 12% when they studied CO_2 and energy efficiency of different heating technologies in the Dutch glasshouse industry for the period 1991–1995. Comparing these results to energy technical efficiency of 74% (Lansink and Ondersteijn, 2006) for Dutch greenhouse firms for the period 1976-1995, one could say that energy use efficiency among Dutch greenhouse firms has improved over time.

Pesticide is found to be the most technically inefficient variable input used under both production technologies. Pesticide inefficiency can be interpreted to mean the degree of stress on the environment. This may also indicate that the management of pesticides by farmers is relatively difficult compared to the other inputs (Oude Lansink and Silva, 2004). The efficiency of pesticides use is dependent on the weather and soil condition of which farmers can manage the least if not impossible. Pest variety and populations can be influenced by changes in temperature, wind, air and humidity conditions thus increasing uncertainties and thus higher and more frequent use of pesticides (Feder, 1979). Also, uncertainties about when and how pests can arrive can be a possible motivation for farmers to overuse pesticides (Skevas et al, 2012). As agricultural production activities are accompanied by significant amount of risks, farmers use pesticides as an insurance policy. High cost of inputs results in increased production costs and consequently increased financial risks. Farmers at this point have a natural tender to protect these investments through increased use of pesticides (Lundgren, 2018). The production of vegetables in particular attracts many different insects, often resulting in farmers overuse of pesticides as a counter-measure (Williamson et al., 2008). Martin et al. (2006) found that for farmers in Sub-Sharan Africa, the overuse of pesticide is further worsened by insecticide resistance. Ngowi et al. (2007) argues that smallholder farmers' overuse of pesticides can be attributed to farmers lack of extension services making them lack knowledge about pesticide use. Previous studies that have reported similarly high pesticide inefficiencies include Skevas and Oude Lansink (2014) and Oude Lansink and Silva (2004) who reported 25% and 32.7% for Dutch arable farms for the period 2003-2007 and 1989-1992 respectively. Singbo et al. (2015) analysed pesticide use among Benin vegetable farmers and found that the farmers could reduce pesticide use by 69% while maintaining the same level of output.

Technical inefficiencies scores of materials and fertilizer also indicate an efficiency gap in the use of these resources. Given that land and other fixed production factors are limited, the efficiency of materials such quality seeds, planting materials and fertilizer are important as they have direct link with output volumes (Abu, 2011). Materials have the highest proportion of variable cost for the sample of outdoor growers and thus a reduction in the inefficiency of materials will contribute significantly to the economic health and competitiveness of the farms.

5.2 Determinants of Input-Specific Inefficiency

The age of outdoor growers has a positive relationship with both energy and pesticide significant at 5% and 10% critical levels respectively. This suggest that as farmers get closer to retirement, they become inefficient in the use of energy and pesticide. The marginal effect values of 0.0011 and 0.0077 implies that a ten-year increase in the age of the farmers is associated with a 0.115% and 0.77% increase in the technical inefficiency of energy and pesticide respectively. This result is consistent with the recent findings of Saiyut et al. (2019) for Thai agriculture. Li and Sicular (2013) suggest a reason that older farmers lack the motivation to improve technical efficiency because they can avoid taking loans to invest in new technology which comes with high risks. However, the evidence on the relation between age and efficiency in the literature is quite inconclusive. Positive relationship between age and inefficiencies has been reported by Skevas et al. (2012) and Mohd Suhaimi et al. (2017) for Dutch and Malaysian agriculture respectively, while Zhengfei and Oude Lansink (2006) and Abatania et al., (2012) have reported the contrary. Studies that have reported a negative relationship between age and inefficiency have explained that older farmers gain experience over the years and hence make better managerial and investment decisions that result in improved performance (Zhengfei and Oude Lansink, 2006; Mathijs and Vranken, 2000). Young farmers on the other hand maybe be efficient as they are more motivated, risk loving and willing to adopt new technologies that increases efficiency (Bozoğlu and Ceyhan, 2007). While some studies have taken sides, others such as Guesmi and Serra (2015) and Ho and Illukpitiya (2014) have concluded that age does not have a relationship with technical efficiency levels among farmers in Spain and Vietnam, respectively.

Short term debt (SD) ratio of indoor growers is found to have a positive relation with the inefficiency of each of the inputs significant at 1% critical level. The marginal effects indicate that a unit increase in the short-term debt ratio is associated with 13.24%, 13.05%, 13.67% 14.13% increase in the technical inefficiency of energy, materials, pesticides and fertilizer respectively. Short term debts are used to meet immediate and liquidity obligations of the farm such as the purchases of variable inputs and paying wages. Thus, undisciplined short-term borrowing might lead to increases in variable inputs and consequently possible inefficient use of them. Zhu and Lansink (2010) also reported positive relationship between short-term debt and technical inefficiency for German agriculture. This is however, inconsistent with the reports of Mugera and Nyambane, (2015) for Australian farmers adding that the cost of borrowing could be a motivating factor for farmers to be efficient. Zhengfei and Oude Lansink, (2006) note that the relationship between short term debt and efficiency is less evident as short-term debts are associated with seasonal and liquidity needs of the farm.

Long-term debt ratio has a negative and significant (1% critical level) relationship with the inefficiency of energy, materials and fertilizer for indoor growers. The marginal effects indicate that a unit increase in the long-term debt ratio is associated with a decrease in the inefficiency of energy by 2.65%, materials by 2.25% and fertilizer by 3.01%. Long-term debt may be used to invest in efficient innovations and technology resulting in improving the efficiency of the farm (Zhengfei and Oude Lansink, 2006). It may also be possible that farms with high long-debt to total assets ratio may be credit worthy as they can provide sufficient collateral to lenders to get loans easily. Its worth noting however, that highly indebted farms may not have access to credit for working capital and therefore may not apply technological processes that improve efficiency (Davidova and Lafruffe, 2007). For the sample of outdoor growers, the above observations are different. The result indicate that long-term debt ratio has a positive and statistically significant relationship with energy and pesticide at 10% critical levels. This could be possible as efficiency of inputs can also be influenced by the weather, example pesticide inefficiency (Feder, 1979). A recent study by Gadanakis et al. (2019) supports this study by showing evidence of the negative relationship between debt to asset ratio and the technical efficiency of Italian cereal farmers.

The degree of specialization measured in terms of the Herfindahl-Hirschman Index (HHI) has different statistical associations with the inefficiency of the separate inputs. HHI for indoor farms has a negative and significant (10%) relationship with the technical inefficiency of energy but positive and significant (1%) relation with the inefficiency of materials, pesticides and fertilizer. As energy is the dominant variable input for indoor growers, they probably enjoy from years of experience in managing energy and from economics of scale at the expense of the other inputs which are relatively used in small quantities. It may be also possible that increased specialization may lead to intensive use of inputs as farmers concentrate on a single activity thus resulting in increased input inefficiency. A similar trend is observed for outdoor growers except that specialization has a negative relation with pesticide inefficiency. Pesticide is the second most dominant variable input after materials and thus an increase in specialization may precipitate benefits of scale economics from the large use of pesticides.

Subsidy is found to have a negative relationship with inefficiencies of all inputs for indoor farmers significant at 1% critical level. This indicates that the motivation for reducing the inefficiency is higher when the farmers receive subsidies. As subsidies are not used for a specific input, farmers can use it discriminately resulting in the differences in the inefficiency of the inputs (Mohd Suhaimi et al., 2017). The relation between subsidy and the technical efficiency of farmers can be double-sided. On one hand it could lead to improvement in the efficiency of farms when subsidies are invested in improving the technology of production (Zhengfei and Oude Lansink, 2006). On the other hand, subsidy reduces farmers motivation to be efficient when they depend on it to a greater extent as an extra income or as an insurance (Zhu et al. 2012). The negative relationship between subsidy and inefficiency inefficiency scores in this study may indicate significant contribution of subsidy to improvement in the production technology of indoor growers. Although the result is in line with the report of Latruffe et al. (2008) for Romanian crop farmers, it is inconsistent with the finding of Rezitis et al. (2003) for Greek agriculture.

Chapter 6

CONCLUSION AND POLICY IMPLICATIONS

6.1 Conclusions

The objectives of this study were to determine the input-specific technical inefficiency among Dutch vegetable farms for the period 2006-2016 and to identify the sources of inefficiencies for the specified inputs. The study employed the Russel type measure of technical inefficiency to compute inefficiency scores for energy, materials, pesticides and fertilizers under constant returns to scale (CRS) and variable returns to scale (VRS) assumptions.

Results from the study suggest considerable inefficiencies in the use of variable inputs among Dutch vegetable farms. This implies that, there is substantial scope for reducing inefficiency in the use of the inputs analysed. Specifically, indoor vegetable growers have mean inefficiencies scores of 0.141, 0.221, 0.235 and 0.228 for energy, materials, pesticide and fertilizer respectively. This indicates that the farmers can reduce their technical inefficiency of energy by 14.1%, materials by 22.1%, pesticide by 23.5% and fertilizer by 22.8% without changing the current output levels. The result indicated that outdoor growers can also reduce energy inefficiency by 8.4%, materials by 4.9% pesticides by 11% and fertilizer by 9.1%. Energy and materials being the most dominant variable inputs used by indoor and outdoor growers respectively were found to be the most efficiently used variable inputs. Pesticide was found to be the most technically inefficient variable input for both indoor and outdoor indicating that pesticides may be the most difficult input to manage by the farmers. These results imply that farmers manage individual inputs differently and thus differences in their inefficiencies can emerge. It was observed that farmers seem to pay more attention to inputs that constitute the highest proportion of total variable cost.

In the second stage of the study, producer specific characteristics that are statistically associated with inefficiencies for the separate inputs were identified. For indoor growers, short-term debt has a positive association with the inefficiency of energy (0.1324), materials (0.1305), pesticide (0.1367) and fertilizer (0.1413). Long term debt is negatively associated with the inefficiency of energy (-0.0265), materials (-0.0225) and fertilizer (-0.0301). The degree of specialization has a negative association with the inefficiency of energy (-0.0241) but positively associated with materials (0.1551), pesticide (0.2650) and fertilizer (0.2523). Subsidy has negative associations with energy (-4.4E-07), materials (-2.3E-07), pesticide (-3.1E-07) and fertilizer (-5.1E-07). For outdoor growers, age of farmers has positive association with the technical inefficiency of energy (0.0011) and pesticide (0.0077). Long term debt has positive relations with the inefficiency of energy (0.1560) and pesticide (0.1219). The degree of specialization has a negative relation with the technical inefficiency of pesticide (0.0658).

6.2 Policy Implications and Future Research

The empirical results have implications for both policy makers as well as farm managers. The noticeable inefficiencies observed for the separate inputs necessitate policy actions to build the capacity of farmers to improve on the use efficiency of these inputs. Government can work with farmers to have joint agreement on the reduction of specific inputs. An example is the 1995 covenant that was signed between the Dutch government and the greenhouse industry requiring the later to have reduced unsustainable energy use by the years 2010. Although the target could not be achieved by the set year, substantial improvement in energy use was recorded. This approach could be replicated for other inputs such as pesticide which has been found to be the most technically inefficient variable input for the sample of vegetable farmers analysed. Alternatively, attention could be paid to producer-specific characteristics that have statistically significant associations with inefficiency of the separate inputs.

The study was limited by an inadequate number of observations. This has the potential to affect inefficiency scores. When the number of observations is inadequate, the number of efficient firms (firms with zero inefficiency) becomes relatively higher resulting in a lower average inefficiency. Another limitation was that few producer-specific characteristics could be found in the given FADN dataset. Data on years of farm managerial experience, the level of education of farm manager, income from non-farm activities and family size are potential farm characteristics that would have been interesting to investigate their statistical associations with inefficiency. Future research could investigate the causality relationships between farm characteristic and inefficiency. The study assessed input-specific inefficiencies in two aspects, technical and scale. Future research could also be undertaken to investigate other dimensions such as cost and allocative inefficiencies.

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