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– a stochastic frontier analysis

Avgörande faktorer för teknisk effektivitet i Svensk nötköttsproduktion
- en stokastisk frontier analys

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Abstract

This thesis presents an estimation of the farm level technical efficiency of Swedish farmers specialized in beef cattle production. The aim is to estimate a score between 0 and 1 which illustrates how efficient the Swedish beef farmers are given the technical assets available. The sample consists of 1200 observations on 296 farms between 2010 and 2016, and the data is collected from farm accountancy data from the EU FADN dataset.

A stochastic Frontier Analysis was made to determine the benchmark of the sample efficiency and the sample mean technical efficiency could then be estimated to 0.64. The results also indicates that conventional farming, older age, availability to grazing area, location of the farm and high levels of support payments are determinants of efficiency.

A negative correlation between the Stochastic Frontier and time was determined, indicating that efficiency has decreased for beef farms over the time period.

Evidence has been found in the literature pointing at the importance of beef production for biodiversity, rural development, economic markets, and the possibility to influence production methods. Thus, the recommendations made in this thesis is for policy makers to understand the drivers of efficiency and to support the factors that improve efficiency to maintain the domestic production of meat.

Keywords: stochastic frontier analysis, technical efficiency, Swedish beef farming, FADN

Sammanfattning

Denna masteruppsats presenterar en uppskattning av teknisk effektivitet inom svensk nötköttsproduktion. Syftet är att uppskatta en poäng mellan 0 och 1 som illustrerar hur effektiva svenska nötköttsproducenter är givet de tillgängliga tekniska tillgångarna inom industrin.
Urvalet består av 1200 observationer på 296 gårdar mellan 2010 och 2016, och uppgifterna samlas in från redovisningsdata från representerade gårdar vilken är sammanställd varje år av Jordbruksverket och inskickad till EU:s gemensamma datanätverk för lantbruksdata; Farm Accountancy Data Network (FADN).

Metoden som användes är en Stochastic Frontier Analysis (SFA) vilken först formulerades av Aigner et al (1977). SFA möjliggör uppskattningen av ett effektivitetsriktmärke för hela urvalet, och uppskattas genom en produktionsfunktion som är representativ för urvalet. Efter det kan den genomsnittliga effektivitetspoängen avgöras som ett mått i relation till det uppskattade riktmärket. Resultatet visar på en teknisk effektivitet på 0,64.

Vidare visar resultatet en positiv korrelation mellan konventionell produktion, ålder, tillgång till betesmark, gårdens lokalisering, utbetalning av jordbruksstöd och effektiviteten på gården. Resultaten visar också en negativ korrelation mellan tid och effektivitetsriktmärket, vilket indikerar en fallande effektivitet bland de representerade gårdarna i urvalet under tidsperioden.

Bevis har inhämtats från litteraturen som pekar på nötköttsproduktionens betydelse för biologisk mångfald, landsbygdsutveckling, ekonomiska marknader och möjligheten att påverka köttets produktionsmetoder efter svenska normer. Således är de politiska rekommendationerna i denna uppsats att beslutsfattare ska förstå drivkrafterna för effektivitet på de svenska nötköttsgårdarna och stödja de faktorer som förbättrar effektiviteten för att upprätthålla den inhemska köttproduktionen.

Table of contents

List of tables

List of figures

Abbreviations

AWU	Annual Work Unit
CAP	Common Agricultural Policy
FADN	Farm Accountancy Data Network
LDI	Livestock Density Index
LR	Likelihood Ratio
MTE	Mean Technical Efficiency
SFA	Stochastic Frontier Analysis
SGM	Standard Gross Margin
TE	Technical Efficiency

1. Introduction

Meat production and consumption has been an increasingly discussed topic within the climate debate. One of the reasons behind this is the level of emissions of Greenhouse gases that are related to the consumption of meat. The consumption of meat, both imported and domestically produced, caused emissions of 2 061 141 kt CO2 equivalents (SCB, 2020). However, meat is an important part of many people's dietary choice, and the Swedish consumption of meat has increased on average by 70% compared to 1990's level of consumption. A reduction in the commodity may cause market, social and environmental changes. (Manevska-Tasevska et al. 2014). Farming activities such as cattle grazing are also crucial to the support of ecosystem services (Garrido et al. 2017). It can also be argued that the consumption of Swedish meat compared to imported is preferred due to tougher animal welfare restrictions in Swedish legislation and lower impact on the environment (Kumm and Larsson, 2007). The average gross margin for Swedish beef producers is among the lowest in the EU both with and without considering the coupled payments (European Commission 2013), and production of beef has decreased by on average 1,6% per year since 1995 (Jordbruksverkets slaktdatabas, 2020).

Efficiency analysis (Battese and Presada, 2002) where cost saving- and efficiency increasing possibilities are evaluated is therefore an important tool both when considering the economical and the environmental future of Swedish beef production. There are mainly four ways in which we can reduce climate impact from meat consumption, one of which is to increase productivity with the efficiency of inputs used (Bryngelsson et al. 2016). Increased efficiency is expected to have positive effects on Swedish beef production in terms of profit margins, environmental footprint and sustainable development in rural regions (Manevska- Tasevska et al. 2014).

1.1. Problem Statement

Swedish beef cattle production is decreasing by on average 1,6% per year (SCB, 2020). Compared to other agricultural production it is also more variable when it comes to farm level economic profit, and the average gross margin for Swedish beef producers is among the lowest in the EU (Manevska- Tasevska et al. 2014). Consequentially, incentives for producers to maintaining today's production level of beef is anticipated to fall even more in the future, which will make it hard for the Swedish Environmental Protection Agency to reach their goals for biodiversity and open landscapes (Kumm and Larsson, 2007). It is also likely to cause an increased level of import because demand for meat among Swedish consumers is still increasing by on average 5% per year (SCB, 2020). An increase in imports will according to Kumm and Larsson (2007) lead to a higher level of environmental impact from Swedish meat consumption. Efficiency analysis provide a good basis for policy makers on understanding factors which promote beef farming on sustainable grounds in the future (Manevska- Tasevska et al. 2014).

1.2. Aim

The aim of this study is to investigate the technical efficiency of Swedish beef cattle production. Factors that are believed contribute to the inefficiency of Swedish beef farms will be presented, and focus will be on the effects of six different elements. The research questions the thesis will address are:

1) What is the average technical efficiency of Swedish beef producers?
2) What are the effects of factors like organic farming, age, farm size, coupled support payments and region where the farm is situated on the average technical efficiency?

The hypothesis is that technical efficiency score of Swedish beef farms will be below 1, 1 indicating 100% efficiency given the set technology level. In a competitive market with free entry heterogenous firms it is very unlikely that all firms operate at 100% efficiency, but equally unlikely that their efficiency would be 0. Above named factors are based on factors used in other similar literature, and found to be of significant impact on efficiency, the hypothesis is therefore that the chosen factors will alter the technical efficiency score from the sample mean.

1.3. Delimitations

The thesis work is limited within the time frame of 20 weeks. Data collection and method for analysis was adapted to fit the time limitations.

The data for the analysis is built on the FADN dataset, and the thesis work is therefore limited to the data available in this dataset. Furthermore, the focus of the thesis is specialized beef cattle, all data on other types of farms is therefore excluded. Farms in other countries, as well as farms not represented in this dataset, are also excluded. The reporting system and processing of data within FADN is extensive and takes years to finish, which is why the most recent data is not yet available. This is the reason why this thesis only uses data between 2010 to 2016.

There are many parametric as well as non- parametric methods to determine Technical Efficiency, this thesis is only focused on the parametric Stochastic Frontier Analysis and will not make any comparisons to other methods.

There are also several sources of inefficiency that could explain the technical efficiency score. For limitation purposes, six factors were chosen as the main inefficiency factors.

1.4. Background and Literature Review

The Following section is a review of the existing literature on technical efficiency and beef farming.

1.4.1. Analytical Framework: Technical efficiency in farming

The stochastic production frontier gives the maximum level of output producible given inputs, the technology, and the production environment. Stochastic frontier analysis is a method used to measure the efficiency of a firm or an organization that uses one or multiple inputs to produce one or multiple outputs. There is cost, profit- and technical efficiency. Technical efficiency of a firm equals the ratio between the actual output given its inputs and the frontier output, being the output that the firm could produce if the right technology were available. The methodology is widely used within agriculture, as it allows for comparisons between firms with the same production function (Kumbhakar, 1987). However, the results in mean technical efficiency (MTE) varies depending on which approach of technical efficiency is being used. Bravo- Ureta et al. (2007) therefore made a meta regression analysis of 167 worldwide studies analysing farm- level technical efficiency, the technical efficiency scores were calculated by stochastic frontiers models, non-parametric and parametric deterministic models.

The results in the study by Bravo Ureta et al. (2007) show that MTE is greater for stochastic models than for deterministic, and that the majority of the studies are parametric models, using panel and cross- sectional data, and basing them on either a trans- log function, or a Cobb- douglas production function. The study also shows a lower MTE using cross sectional data rather than panel data but cannot determine the relevance of the choice of functional form. MTE is also positively correlated to average country level income. What the study also concludes is that improvements in technical efficiency as a means of increased productivity has more potential in countries in Eastern Europe, Africa, Asia, and Latin America than it has for countries in western Europe and North America (Bravo Ureta et al. 2007).

Although the relationship between technical efficiency and productivity increase is only slightly positive for western European countries, the model can still be useful when looking at the impact on efficiency for specific inputs. In a study by Latruffe et al. (2017) stochastic frontier technical efficiency is used to measure the impact of EU subsidies (CAP) on the technical efficiency of 9 dairy farms in Western European countries, with data from the Farm Accountancy Data Network (FADN) stretching over 18 years. They compute a Cobb- Douglas stochastic production frontier using a single output, and four inputs. In this study they also point out the risk endogeneity. Endogeniety arises when farmers adapt inputs used in response to stochastic events affecting their production. If not addressed in the production function, there is a risk of correlation between the input terms and some of the error term. They address this problem through introducing a “method of moments” estimation for the endogenous term.

The study by Latruffe et al. (2017) present evidence for the effects of subsidies on technical efficiency of dairy farming, both before and after decoupling. The results show different effects depending on in which country the dairy farm is located. Belgian, and British farms show negative correlation between technical efficiency and introduction of CAP subsidies, whereas dairy farms in Spain Italy and Portugal show positive correlation. Danish, German, Irish and French farms show no correlation. As the CAP- subsidies aims at improving both productivity in European farming, but also the living standards of farmers, then technical efficiency can measure the impact on both, and therefore be an informative tool for policy makers (Latruffe et al. 2017).

There have also been technical efficiency studies on Swedish farming. According to Zhu et al. (2012), larger size, higher degree of specialization, lower share of family labour, more rented land, and lower degree of indebtedness increase technical efficiency in Swedish dairy farms. Another study by Zhu et al. (2010) shows that the technical efficiency of Swedish crop farms between 1995- 2004 was 71% and that the biggest contributor to TE is farm size.

Factors such as managerial behaviour (Manevska Tasevska and Hansson 2011), farmer's experience and knowledge (Manevska Tasevska 2013), information available, and intensity of data recording, budgeting, and monitoring of results (Manevska Tasevska and Hansson 2011) have been found to affect technical efficiency in several Swedish studies.

Manevska- Tasevska et al. (2017) made estimations of both residual (RTE) and persistent technical efficiency (PTE) in Swedish pig farming. The difference in measuring RTE and PTE instead of the overall technical efficiency (OTE) is that PTE is the relation between TE and farm specific factors such as managerial practices, whereas RTE is related to time varying residual factors. PTE is likely to be persistent over time and subject to change only if there are profound changes in the management practices on the farm. RTE, on the other hand, may change over time and is likely to do so because of random factors such as weather conditions, market, and policy changes, etc. but also because of the farmer's experience. The study by Manevska Tasevska et al. (2017) brings evidence to the importance of separating persistent and residual efficiency when the influence on efficiency of variables with an accumulated effect, such as management practices, is being analysed.

1.4.2. Theoretical Background: Beef Farming

Beef production in Sweden consists of two business models, either as a bi-product of milk production; all animals not directly producing milk are slaughtered for beef, or as a model where production is specialized on beef, which is the single output of production. This study will be focused on the latter.

Swedish beef cattle production generally consists of the calves annually born by every beef cow. Traditionally Sweden has had a smaller herd of beef cows relative to dairy cows. In the mid 1980's there were 60 000 beef cows in Sweden, compared to 650 000 dairy cows. However, over the last two centuries there has been a shift in production, leading to a decrease in the dairy cow herd to 400 000 while the beef cow herd has increased to 170 000. This shift can be explained by a shift in consumption patterns, but mainly the increase in beef cows has been the result of a major policy change in 1990 where subsidies in extensive grazing increased relative to other agricultural actions. Since the year 1990 the herd of beef cows has been rather steady at 150 000 cows, while the herd of dairy cows decreases at constant annual rate. So far, because of the increase in beef cows, and a simultaneous increase in the carcass weight at slaughter, beef production in Sweden remains steady despite the decrease of dairy calves provided to the beef market. However, this is not a sustainable level unless efficiency in beef production increases, or we increase the herd of beef cows (Kumm and Larsson, 2007).

Compared to other meats, Swedish consumption of beef is relatively high. Only pork meat is consumed more. Consumption of beef has increased from 18,3 kg Person/ year in 1980 to 22,5 kg/ year in 2020 (jordbruksverkets statistikdatabas, 2020).

Sweden’s degree of self-sufficiency is today 55% (LRF, 2020), which means nearly half of total beef consumption comes from imports. According to Kumm and Larsson (2007) this means we import meat produced with less environmentally sustainable means, mainly because of the difference in fodder intensity between productions in different countries. According to Kumm and Larsson (2007) land prices is the main impacting factor. This means that in a country like for example Brazil, where land prices are relatively low compared to meat producing countries like Ireland and Sweden, the costs of extensive beef production are not as high per hectare.

1.4.3. Technical efficiency in beef production

Latruffe et al. (2006) investigated technical efficiency of beef and crop farms in Poland. At the time of the investigation Poland was a candidate for the European Union and its agriculture suffering from structural problems, characterized by many small holdings, high employment density per hectare and few farms that were market sustainable. Mean technical efficiency was estimated both with a parametric and a non-parametric method and concluded to be 0,88. The factors of inefficiency were soil quality, age, degree of market integration, and share of hired labour. It was found that beef farms were more technically efficient than crop farms, big farms more efficient than small farms, and soil quality and market integration were large determinants of inefficiency. It was also concluded that the share of hired labour was smaller on beef farms because the relied more on unpaid family labour.

Martinez- Cillero et al. (2017) computed a stochastic production frontier for Irish specialized beef farming using a panel dataset comprising detailed accountancy data between the years 2000 and 2013, and focusing on the effects of CAP reforms. They use output quantity (kg meat/ year) as dependent variable, and capital, variable costs, land area and labour as input variables. Their results indicate that technical efficiency in the beef farming sector has been poor, with an average efficiency score of only 0.53 during the period. However, they found that direct income received in the form of coupled payments had a positive impact on farm efficiency, and that this positive effect was maintained after their replacement with decoupled income support.

Manevska- tasevska et al. (2014) studied the cost saving possibilities of Swedish beef farming using both classical radial distance function (CRDF) and the generalized directional distance function (GDDF) non- parametric approach to technical efficiency frontiers. Farm size, Livestock Density and Structure, self-sufficiency, and organic farming, as well as loans, investments, subsidies and regional differences are factors of inefficiency looked at in this paper. They find that costs can be saved up to 20%. They also conclude that technical efficiency analysis has been absent within the Swedish beef production field prior to the study.

1.4.4. Motivation of the Study

Technical efficiency has been widely examined in Europe and in Sweden within Dairy farming. This Master Thesis contributes with novel research within the field of beef production. There are several factors pointed out in this thesis why domestic production of beef is important to maintain. Knowing the technical efficiency of a certain industry and the drivers behind it can help policy makers improve domestic production and support more sustainable methods. It is therefore important to know why Swedish beef production is decreasing while demand for meat is increasing, and the answers could lie in the determinants of the technical efficiency.

2. Methodology

Efficiency in economics is often estimated by specifying a group within a sample as the most efficient, then using this group as a benchmark for efficiency within the rest of the sample. There are two standard ways of measuring efficiency; Data Envelopment Analysis, which is a non- parametric approach and will not be further specified by this thesis, and Stochastic Frontier Analysis, which estimates a mathematical production function as a benchmark for efficiency (Gralka, 2018). The following section specifies the methodology used in this thesis work and is mainly based on the book *A Practitioner's Guide to Stochastic Frontier Analysis using STATA* by Kumbhakar et al. (2015), and the book *An Introduction to efficiency and Productivity Analysis* by Coelli et al. (2005) with some additional notes from Gralka (2018), Bravo- Ureta et al. (2007) and Battese (1992).

2.1. Stochastic frontier analysis

Stochastic Frontier analysis uses econometric models to estimate production frontiers. Once a frontier is estimated, efficiency can be measured relative to the frontier. Efficiency is defined as the ratio between actual output and maximum potential output. In the context of production efficiency, output is a function defined by given inputs and technology, and the deviation of actual output from the optimal efficiency frontier is explained by technical inefficiency. It is important to note that the technical efficiency frontier is unobserved, so it is rather an estimation of given parameters. The frontier is also viewed as stochastic, which means it has a randomly distributed probability and cannot be estimated precisely (Kumbhakar et al. 2015). The methodology for the Stochastic Frontier Analysis used in this thesis can be described in four simplified steps:

1.) Estimating the production function representative for given sample
2.) Estimating the stochastic frontier production function using econometric modelling
3.) Determining the technical inefficiency between actual and optimal production
4.) Determining the technical efficiency score

2.1.1. Definition of Stochastic Frontier and Technical Efficiency function

There are two ways in which one can analyse the frontier data, deterministic or stochastic. The stochastic and deterministic viewpoints take its base in the same variables, but the stochastic viewpoint allows for random errors, which can provide a more realistic result. The stochastic model is hence derived from the deterministic function, which is why this section starts by defining the deterministic frontier model. Furthermore, the nature of the panel data used in this thesis (and further described in chapter 3) is too unbalanced for a feasible log-likelihood estimation, hence all equations are defined by cross- sectional data.

Equation 1: simple production frontier model

$$Y_i = F(x_i;\beta) * TE_i$$

where
Y_i: is the scalar output of producer i, i = 1, 2, ..., I.
x_i: is the vector of N inputs used to produce y.
F(x_i;β): is the production frontier
β: is a vector of the technology parameters that are to be estimated.
TE_i: is the output oriented technical efficiency of producer i.

The Deterministic production function can be defined as:

Equation :2 deterministic production frontier

$$TE_i = \frac{Y_i}{F(x_i;\beta)}$$

Which describes technical efficiency of producer i, TE_i, to be equal to the ratio of the observed output, Y_{it}, and the maximum feasible output, f(x_i;β). The equation further describes that the observed output can achieve a maximum feasible value of output if and only if TE_i=1. If TE_i< 1, it will measure the difference between the observed output and maximum feasible output.

When the production frontier model is deterministic it will ignore random shocks that can affect the producer and thus the output. In order to include the random shocks to the output and producer, the deterministic production frontier is rewritten with the component of exp{v_i} and thus one gets the stochastic production frontier model:

Equation 3: Stochastic frontier model

$$Y_i = F(x_i; \beta) * \exp\{v_i\} * TE_i$$

Where $f(x_i;\beta)$ is the deterministic part of the stochastic production frontier which is common to all producers and the stochastic part that catches the random shocks is $exp\{v_i\}$, which is unique for all producers. The stochastic production frontier can be rewritten into:

Equation 4: stochastic production frontier

$$TE_i = \frac{Y_i}{F(x_i; \beta) * \exp\{v_i\}}$$

Stochastic and Deterministic equations for TE_i are rather similar, but there is a difference regarding when the producer is technical efficient or not. For the stochastic version technical efficiency is the ratio of the scalar output of producer i and the maximum feasible output and the random shocks that could occur. However, the producer will achieve the maximum feasible output if and only if $TE_i = 1$. If $TE_i < 1$, it will measure the difference between the observed output and maximum feasible output. The difference will be measured in the environment of the stochastic component, $exp\{v_i\}$, which is allowed to be different from producer to producer. As it includes the effects of random shocks in the producer's environment it will be preferred.

The single-output stochastic production frontier can be written as:

Equation 5: single output stochastic production frontier

$$Y_i = F(X_i; \beta) * \exp\{v_i - u_i\}$$

Where $TE_i = exp\{-u_i\}$ and $exp\{v_i\}$ is the random-noise error component (Kumbhakar et al. 2015).

2.1.2. Definition of Technical Inefficiency

The decomposed error term in equation 5 consists of the random noise and the inefficiency component, which is estimated in a separate function, and can be defined as:

Equation 6: Technical Inefficiency Function (Battese and coelli, 1995)

$$u_i = z_i \gamma + w_i$$

Where z_i is a vector of explanatory variables related to inefficiency, which are defined as efficiency determinants in this thesis, γ is estimated parameters of the determinants, and w_i is a random unknown variable.

There are three main problems estimating efficiency in cross- sectional data. First, inefficiency estimates depend on distributional assumptions for v_i and u_i. Second, u_i and v_i has to be independent from the other regressors. This is unlikely to hold since a profit maximizing firm is likely to change inputs as far as possible given changes in external factors. Third, mean or mode of $u(v-u)$ never approaches u as number of firms increase (Kumbhakar et al. 2015).

2.2. Assumptions

Within the concept of Stochastic Frontier Analysis, a set of assumptions need to be made, which are specified in the following section.

2.2.1. Type of Function and functional form

Stochastic Frontier Analysis can be based either on a Production-, Cost-, Profit- or Distance function, where production function is the preferred function for the efficiency analysis in this thesis, since it enables a comparison of one output subject to several inputs. It is important to note however, that it is only able to determine the technical efficiency of inputs using the production function. No assumptions can be made on the allocative efficiency of observed inputs (Gralka, 2018).

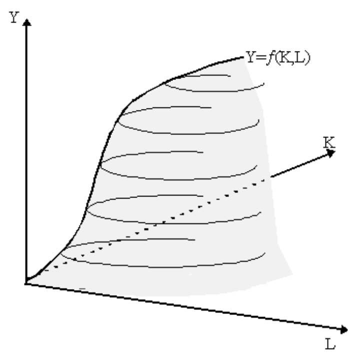


Figure 1: A production function with two inputs and one output (Kumbakhar et al. 2015)

Figure 1 illustrates a classic production function of output Y using inputs K and L. The surface of the quasi- concave curve along with the grey coloured area below represents the feasible production set, meaning it contains all the feasible combinations of K and L to produce Y under a given technology level. The production function curve Y=f(K,L) represents the maximum output achievable, hence the frontier. In standard production theory it is a basic assumption that all production activities are on the frontier. In production efficiency analysis however, this assumption is relaxed and the fact that producers may be below the frontier due to technical inefficiency is considered (Kumbhakar et al. 2015).

A production plan is technically inefficient if production is located below the estimated frontier. However, this estimate is conditional on given technology level, and could be proven efficient given a different technology. The implication is that if a single common production function is estimated, the data should contain only those in the sample that share the same technology, unless heterogenous technology can be taken into account in the specifications of the production function (Kumbhakar et al. 2015).

The frontier equation is defined as:

Equation 7:Stochastic frontier

$$Y_i = F(X_i; \beta) * \exp\{v_i - u_i\}$$

Where $f(x_i;\ \beta)$ is the production function for a vector of given inputs (x) and technological change (β) (Battese, 1992). Once the type of function has been determined it is also important to note that the functional form used is an important factor that affects the analysis of efficiency. The most used functional forms within the Stochastic frontier Analysis are the Cobb- Douglas production function and the trans- log function (Bravo- Ureta et al. 2007).

The Cobb- Douglas production function in linear form with technological change can be defined as:

Equation 8:Cobb- Douglas Production function

$$lnY = \beta_0 + \sum_j \beta_j lnx_j + \beta_t t$$

And the trans- log production function in linear form with technological change can be defined as

Equation 9: trans- log production function

$$lnY = \beta_0 + \sum_j \beta_j lnx_j + \frac{1}{2}\sum_{kj} \beta_{jk} lnx_j lnx_k + \beta_t t + \beta_t t^2$$

Technical change in both equations is given by

$$\frac{\partial lny}{\partial t}$$

And the rate of technical change is given by

$$\frac{\partial'' lny}{\partial t}$$

In the way that the Cobb- Douglas function is built, the first order derivative becomes β_t and the second order derivative becomes zero. The implication of this relation is that the Cobb- Douglas production function assumes a constant rate of technological change over time. In practice, however, technological change can vary in impact between time periods. In the trans- log functional form, the time trend is introduced in such a way that it allows for some change over time in the slope coefficients, hence it becomes more flexible, which is why the trans- log functional form is favoured (Kumbhakar et al. 2015).

The choice of functional form will also be tested using the *likelihood ratio test* described in chapter 3 which evaluates the goodness of fit of the two models.

2.2.2. Distribution of the Efficiency term

The frontier equation is defined as:

$$Y_i = F(X_i; \beta) * \exp\{v_i - u_i\}$$

Where v_i is the stochastic noise component and u_i the error term, and $exp(v_i\text{-}u_i)$ is the total error component. The distribution of v_i and u_i determine how much the error term affects the model, hence can vary the results of the estimation. For a cross- sectional dataset the assumptions made about distribution are very important since they determine what can be defined as inefficiency and what is just statistical noise. For this method the normal exponential distribution of u_i is assumed.

3. Data

The thesis is based on a panel dataset with 1200 observations of Swedish farms specialized in beef cattle for fattening and rearing. The observations are made on 296 farms between the years 2010 and 2016, the panel is unbalanced, which means there are not the same number of observations on each farm. One farm appears on average 4 years in a row. The source of the data is the Farm Accountancy Data Network (FADN) which is an EU-level data network that collects annual farm level accountancy data from all its member states. FADN is the only standardized survey- based farm- level dataset in Sweden and is commonly used for efficiency analysis of farms. The Swedish FADN dataset is a rotating unbalanced panel, the sample is stratified on farm size and geographical location. Each year about 1000 farms are randomly selected to represent the 30000 biggest farms in Sweden, all categorized and coded after type of farm. The sample for this thesis was then selected based on the FADN standardized coding for specialist beef cattle for fattening and rearing (code 460).

3.1. Input variables and data description

To estimate farm- level efficiency, a model with one output variable as well as five input variables was made. Output (Y) consist of sales value of all animal types annually sold for slaughter on the farm and is expressed in SEK. The five input variables were constructed based on the typical production characteristics of Swedish beef systems, and are defined as follows:

X_1= Labour expressed in Annual working Units
X_2= Area Utilized in ha
X_3=Herd Size expressed in Livestock Density Unit (number of Livestock units per hectare)
X_4= Intermediate costs in SEK
X_5= Fixed costs in SEK

A further description of the variable content and how they are linked in the FADN dataset is shown in appendix 1.

Labour, land use, and livestock number is used as an input in many cases of beef farm technical efficiency in the literature, see for example Manevska- Tasevska et al (2014), Martinez- Cillero et al (2018), Latruffe et al (2006). Converting total labour hours into Annual Working Units is a simple way to let the data express what the labour effort represents in value of full-time workers (Latruffe et al. 2006).

Area utilized is expressed in hectares and defined as the area of grazing and grass production that is used. Total land area of the farm is assumed to be irrelevant in this case as it is not directly related to the output of meat. A ratio of bought fodder over the farm's own production of fodder is used as a variable to control for land which is omitted in the X_2 variable but still linked to the production of meat.

Livestock Density Units (Kothman, 1974) was chosen as a variable for Herd size as it expresses not only the number of animals used as input in production, but also indicates how much space each individual use. This is relevant to the study as the legislation on grazing for beef cattle is different in Sweden compared to other countries (Swedish Board of Agriculture, 2020), and might affect the efficiency of herd size.

Capital Use is used as input variable in varied ways in the studies mentioned above. As this study is based on Swedish accounting data, capital use was easiest identified through accounting data on intermediate and fixed costs. The choices and values of intermediate and fixed cost variables are closely linked to cost variables in Manevska- Tasevska et al. (2014). All input variables are expected to be positively linked to efficiency.

Table 1: Input variables and data description

Variable	N	Mean	SD	Min	Max
Output	1200	762,000	1,040,000	4530.79	7,770,000
X_1 Labour	1200	1.79	1.12	0.06	6.53
X_2 Area Utilized (ha)	1200	105.37	100.34	2.20	797.20
X_3 Herd sized (LDI)	1200	0.72	0.75	0.01	8.27
X_4 Intermediate Costs	1200	1,210,000	942,000	136,000	4,890,000
X_5 Fixed Costs	1200	361,000	342,000	4297.49	1,910,000
Bought/produced fodder ratio	1200	0.17	0.19	0	1

Mean output is 762,000 SEK, which is higher than the mean represented on the FADN website (48722 EUR) but lower than in the study by Manevska Tasevska et al. (2014) where mean output is 934,367 SEK. The figures are based on the same dataset, but not entirely comparable since they are computed during different years. As is also mentioned by Manevska- Tasevska et al. (2014) output of Swedish beef farms varies. This can have many explanations, but one likely explanation is that approximately 25% of farmers in Sweden are full time employed in their agriculture (Swedish board of agriculture, 2016). This trend can also be seen in the data on labour, where 25% of the variables in the dataset has a value of AWU under 1, where AWU=1 equals one fulltime worker/ year. The implication of this is that there are many smaller holdings represented in the dataset. The average farm size in ha is 105, and on average 17% of fodder consumption is bought from another producer.

A Livestock density index >1 and <2 defines the herd size as a deferred rotation system, which provides for a systematic rotation of the deferment among pastures (Scarnecchia et al. 1982). The average herd size expressed in LU was 62.

A variable *t* is also included in the model to account for time variance. *t* can take on values between 1 and 7 where 1 represents the first observed year of the sample, which is 2010, hence 7 represents 2016.

Several observations had to be dropped due to zero values. 70 out of the 1308 observations had zero output. The explanation to this is most likely an error in accounting data; the output of these farms is accounted for under a different coding. Since no regression or frontier can be made if the dependent variable is zero, they were omitted. There were also some variables that were greatly larger than the mean, creating a biased result. The omitted outliers are specified in table 3.

Table 2: outliers

Observations with code 460:	**1308**	
Variable Name	**No of drops missing value**	**Outliers**
Output	70	26
LDI	3	0
Area utilized	0	0
Fixed costs	1	0
Intermediate Costs	0	17
Labour	0	6
N observations after omitting outliers:	**1185**	

3.2. Inefficiency factor variables and data description

A number of farm characteristics that are likely to affect inefficiency were added to the model, both continuous and dummy variables. Variables that capture effects from the farm's economic structure is a dummy variable for total support payments above the mean of the sample, and a ratio of total farm dept over produced output. Farm dept and support payments are used in Manevska-tasevska et al. (2014), and introducing variables as ratios of outputs by Bojnec and Latruffe (2009). Taking the additional income from crops into account is commonly done by introducing it as a second output (Manevska Tasevska et al. 2014; Martinez- Cillero et al. 2018). Here it is introduced as an inefficiency factor which is expected to significantly decrease inefficiency. Land quality is accounted for by dividing the sample into three regions depending on FADN regional coding: code 710 South (Skåne, Halland, Blekinge), code 720 Middle (Stockholm, Uppsala, Sörmland, Östergötland, Jönköping, Kronoberg, Kalmar, Gotland, Västra Götaland, Värmland, Örebro and Västmanland) and code 730 North (Dalarna, Gävleborg, Västernorrland, Jämtland, Västerbotten and Norrbotten). There is also an additional variable for Less Favourable Land, a coded variable where 1= farm not situated in LFA area, and codes 2-23 means majority of farms are located in LFA area. LFA is expected to have a positive effect on inefficiency, and the area codes are expected to have a less positive effect on inefficiency on the lower coding.

Dummy variables for organic and conventional farming was created from FADN codes 1 (conventional) and 2 (organic). Organic farming is expected to have a positive effect on inefficiency.

The age dummy variables are created from data on birth year of the owner or user of the farm. Tables 4, 5 and 6 are descriptive statistics of the inefficiency determinants used in the model.

Table 3: continuous inefficiency determinant

Variable	N	Mean	SD	Min	Max
Debt/ output ratio	1200	10.43	39.54	0.00	773.76

Table 4: Dummy inefficiency determinants

Age	Freq	Percent
Age<60	475	44
60<Age	602	56
total	1077	100
Region		
South	739	62
Middle	350	29
North	111	9
Total	1200	100
Organic		
Organic	361	30
Conventional	656	55
Other	183	15
total	1200	100
Highsupport		
Supportpayments>900,000	407	34
Supportpayments<900,000	793	66
total	1200	100
Grazing Area		

3.3. Hypothesis Tests

One of the drawbacks of estimating parameters to determine the stochastic frontier is having to specify functional form representing the production technology and imposing assumptions on the error components of the model. It is important to ensure that the model specification correctly represents the data. Therefore, in addition to the results several hypothesis tests will be run:

Hypothesis 1: H_0: $\beta_{jk} = 0$

the null hypothesis that identifies an appropriate functional form between the restrictive Cobb-Douglas and the trans- log production function. A likelihood ratio test will determine whether the coefficients on square and interaction terms of input variables are not statistically different from zero. A cobb- Douglas production function is one where these terms are zero, and hence will be preferred if H_0 cannot be rejected.

Hypothesis 2: H0: $\gamma_0 = \boldsymbol{\gamma}_1 = \boldsymbol{\gamma}_2 \dots \boldsymbol{\gamma}_n = 0$

the null hypothesis specifies that the influence of identified inefficiency factors is zero and will be determined through an LR-test.

Hypothesis 3: H0: $ui = iid\ N+(0, \sigma u\ 2)$

The null hypothesis specifying that normal exponential distribution better fits the model as opposed to the alternative case which assumes truncated normal and exponential distribution for the u_i and will be determined through comparing log- likelihoods of the models.

Hypothesis 4: H0: $\sum \beta i = 1$ i={1,2,3,4,5}

The null hypothesis specifying that there exists constant return to scale in the production function. A simple summary of the input's first order coefficients will determine whether the production function exhibits a constant, increasing, or decreasing returns to scale.

Log- Likelihood ratio test

A Generalized log-likelihood ratio (LR) test can be used to test which specification better fits the data. The Generalized log-likelihood ratio test is given by:

$LR = -2[\ln\{L(H0)\} / \ln\{L(H1)\}] = -2[\ln\{L(H0)\} - \ln\{L(H1)\}]$

Where L(H0) and L(H1) are the values of the likelihood functions under the null (H0) and alternative (H1) hypothesis respectively. The computed test statistics should be compared with critical values of the mixed chi-square distribution. The LR and Wald tests are applied using the lrtest and test command in STATA.

4. Econometric Results and Discussion

The analysis was conducted using the package *reg* and *sfcross* in the STATA IC program. A non- linear regression was made using both the cobb- douglas and the trans- log production function discussed in chapter 3. Performing the LR- test resolved in a trans- log production function with an adjusted R- squared of 0.64 and all coefficients positive in the first order. An important notice is that the labour input variable x_1 was not significant.

4.1. Hypothesis tests

Table 5: Hypothesis tests

Hypothesis	Test	Decision
1:H_0: β_{jk} =0	Likelihood Ratio	Reject H_0
2:H_0: $\gamma_0 = \gamma_1 = \gamma_2 \ldots \gamma_n$=0	Likelihood Ratio	Reject H_0
3:H_0: $ui = iid\ N$ +(0, σu 2)	Log likelihood	Reject H_0
H_0: $\sum \beta i$ = 1 i={1,2,3,4,5}	Simple summation	Cannot reject H_0

Hypotheses 1-3 determine the goodness of fit of the model. All hypotheses were rejected, which motivates the choice of a trans- log function over a Cobb-Douglas function, and the addition of inefficiency determinants. Furthermore, the model with exponential distribution showed a larger wald- chi statistic than the half- normal distribution. The model with truncated distribution was not concave.

Hypothesis 4 cannot be rejected; hence the production function does not demonstrate constant returns to scale. As the sum of β_i=1.57 there is increasing returns to scale present, that is, as all input variables are increased by one unit, output is increased by 1.57 units. According to Coelli et al. (2007) increasing returns to scale could indicate scale inefficiency, hence some of the inefficiency of the model could be explained by the fact that the farms in the sample are too small in their operation to be fully efficient given the available technology.

4.2. Stochastic Frontier

Furthermore, a stochastic frontier for cross- sectional data both with and without the inefficiency determinants was constructed. A second LR- test determined that the inefficiency determinants significantly contributed to the model, resulting in the following function for the stochastic frontier:

Equation 10:Estimation of Stochastic Frontier Model

$$lnY = \beta_0 + \sum_{j=1}^{5} \beta_j lnx_{ji}$$
$$+ \frac{1}{2}\sum_{j=1}^{5}\sum_{k=1}^{5} \beta_{jk} lnx_{ji} lnx_{ki} + \partial_1 \left(\frac{Bought}{produced} fodder\right)_i + \partial_2 \ln(t)_i + \partial_3 \ln(t)_i^2$$
$$* \exp\{v_i - u_i\}$$

And the after following Inefficiency Function:

Equation 11: estimated inefficiency function

$$u_i = \gamma_0 + \gamma_1(organicDummy) + \gamma_2(NorthernRegionDummy)$$
$$+ \gamma_3(HighSupportDummy) + \gamma_4\left(\frac{Dept}{output}\right) + w_i$$

The results from the STATA IC output of the stochastic frontier are presented in table 6. The results show that all input coefficients are positive in the first order, but labour is negative in the second order, implying a diminishing marginal efficiency of labour. A larger ratio of bought fodder over farm- produced fodder show a positive coefficient on the frontier as well, similar to the self sufficiency variable in Manevska- Tasevska et al. (2014).

The largest impact on efficiency is the size of the herd. A 1% increase in herd size is expected to increase output with 0.58%. A different result was found by Manevska Tasevska et al. (2014), where the coefficient for LDI was 0.01. However, they find that putting that figure in relation to how many grazing days the herd has per year increases the coefficient to 0.21. In their paper, they link the importance of herd size on efficiency to the scale properties of the industry. Lower importance of herd size is linked to decreasing returns to scale. The characteristics of returns to scale in this thesis' model is discussed further in section 4.4.

Another important factor of efficiency is intermediate costs. A 1% increase in intermediate costs is expected to increase efficiency by 0.48%. The corresponding variable in Martinez- Cillero et al. (2017) is variable costs, and the coefficient is 0.36%. Latruffe et al. (2004) show a coefficient of 0.86%, however, all intermediate consumption is weighted in that variable which is expected to increase its coefficient. The conclusion that can be drawn is that investments in the farm both in the long and short run has an important and positive impact on efficiency.

The coefficient for Area utilized show an increase in output of 0.34% which is expected from the similar literature by Latruffe et al. (2004) where the corresponding coefficient is 0.18% and Martinez Cillero et al. (2017) where it is 0.36%.

Looking at the vector of inefficiency determinants one can conclude that organic production, firms operating in the north region, and a higher ratio of dept over output are positively correlated with inefficiency, hence negatively correlated with efficiency, which is generally supported by the results by Manevska-Tasevska et al. (2014). Firms with coupled support- payments over 900,000 however show opposite correlation, implying that support payments are positively correlated with efficiency.

The coefficient for t is negative, indicating that average technical efficiency has been decreasing over time during the sample time period.

Table 6: Estimated coefficients of the stochastic frontier

VARIABLES	Symbol	Coefficient	Standard Error
Frontier			
ln(Labour)	β_1	0.051	0.057
ln(AreaUtilized)	β_2	0.223***	0.059
ln(HerdSize)	β_3	0.578***	0.046
ln(IntermediateCost)	β_4	0.482***	0.069
ln(FixedCost)	β_5	0.231***	0.048
$(\ln Labour)^2$	β_7	-0.198**	0.097
$(\ln AreaUtilized)^2$	β_8	0.340***	0.114
$(\ln HerdSize)^2$	β_9	0.180***	0.038
$(\ln IntermediateCosts)^2$	β_{10}	0.179	0.185
$(\ln FixedCosts)^2$	β_{11}	0.177***	0.060
lnLabour*lnAreaUtilized	β_{12}	-0.159*	0.087
lnLabour*lnHerdSize	β_{13}	0.072	0.052
lnLabour*lnIntermediateCosts	β_{14}	0.019	0.112
lnLabour*lnFixedCosts	β_{15}	0.094	0.063
lnAreaUtilized*lnHerdSize	β_{16}	0.235***	0.053
lnAreaUtilized*lnIntermediatecosts	β_{17}	-0.104	0.112
lnAreaUtilized*lnFixedCost	β_{19}	-0.132*	0.068
lnHerdSize*lnIntermediateCosts	β_{20}	-0.164**	0.064
lnHerdSize*lnFixedCosts	β_{21}	-0.065*	0.039
lnIntermediateCosts*lnFixedCosts	β_{22}	-0.123	0.085
(Bought/produced fodder ratio)	δ_1	0.159***	0.014
ln(t)	δ_2	-0.066	0.108
$\ln(t)^2$	δ_3	0.032	0.054
Constant	β_0	0.599***	0.067
Usigma	γ_0	-1.873***	0.172
OrganicDummy	γ_1	1.067***	0.175
NorthernRegionDummy	γ_2	0.324	0.272
HighsupportpaymentDummy	γ_3	-0.713***	0.204
Dept/output ratio	γ_4	0.032***	0.004
Vsigma	α_0	-1.713***	0.095
Observations		1,185	

*** p<0.01, ** p<0.05, * p<0.1

4.3. Technical Efficiency

Mean Technical efficiency for the whole sample was estimated to 0.64 or 64%. This means that on average Swedish beef farms are 36% inefficient compared to the technical efficiency frontier. The statistics of the estimation are shown in table 7.

Table 7:Sample Mean Technical Efficiency

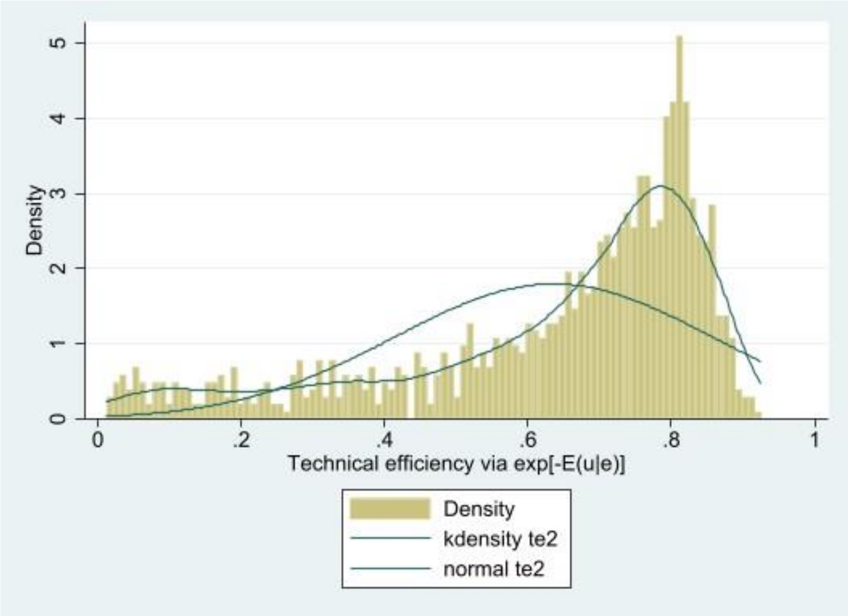
Variable	N	Mean	SD	Min	Max
TE- score	1,185	0.64	0.22	0.01	0.93

This technical efficiency score is significantly lower than the scores presented in the literature. The Swedish corresponding literature by Manevska Tasevska et al. (2014) present a TE score of between 0.75 and 0.82. Latruffe et al. (2004) presents a TE score of 0.88 and Martinez- Cillero et al. (2017) a score of 0.74. Bravo- Ureta et al. (2007) found in a meta regression analysis on technical efficiency studies that parametric analyses often give lower mean TE than non-parametric analyses.

Figure 2 show the distribution of technical efficiency within the sample. Graphically it can be concluded that the estimated density of the sample is distributed around a technical efficiency score of 0.8. However, approximately 32.5% of the sample presents a technical efficiency score below 0.6, creating the lower bound tail presented in the histogram. Approximately 3.7% of the sample presents a technical efficiency score below 0.1, which is not explained by the data.

One possible explanation for the anomaly in the data can be found in the paper by Martinez- Cillero et al. (2017). In this paper the data is divided into two cattle sub- systems based on the enterprise’s Standard Gross Margin (SGM). The “Cattle Rearing” group has a SGM where 50% or more originate from beef. The “Cattle Other” has a SGM where 50% or less originate from beef. The “Cattle Other” *presents* a higher distribution close to zero while the “Cattle rearing” group present an average TE score of 0.74. It might give a more representative result if the data in this thesis could be grouped in a similar way.

Figure 2 histogram of distribution of technical efficiency score over the sample, with normal mean TE and Kernel mean TE represented in curves.



4.4. Efficiency Determinants

Table 8: TE score Efficiency Determinants

Efficiency Determinant	Obs	Mean TE	Std. dev	Min	Max
Organic	361	.52	.25	.01	.88
Conventional	656	.69	.19	.03	.93
Region South	677	.63	.22	.01	.93
Region Middle	335	.65	.23	.01	.90
Region North	101	.60	.24	.02	.89
Age>60	602	.64	.20	.03	.93
Age<60	475	.62	.24	.01	.91
Support payments> 90,000	389	.67	.22	.02	.93
<90,000 SEK	727	.62	.22	.01	.91
Grazing area>100 ha	402	.64	.23	.02	.93
<100 ha	714	.64	.22	.01	.91

The TE scores were sorted in sample groups after characteristics further described in section 3.2. This enables an analysis of contribution to Sample TE- score from the different determinants. Here the groups of the sample can be compared, and it can be determined that conventional farms are more efficient than organic farms.

Furthermore, region Stockholm, Uppsala, Sörmland, Östergötland, Jönköping, Kronoberg, Kalmar, Gotland, Västra Götaland, Värmland, Örebro and Västmanland is more efficient in beef farming compared to other parts of Sweden. This is not the same result as in Manevska Tasevska et al. (2014). The explanation to this is most likely that the difference is so small between the regions that it is only dependent on the random sampling.

If the owner or user of the farm belongs to the age group over 60 years old, the farm is more likely to be efficient. Age presents a positive coefficient both in Martinez- Cillero et al. (2017) and in Latruffe (2004). This can also be supported in findings by Manevska Tasevska (2013) where the findings are that knowledge and experience are key determinants of farm level efficiency.

If the level of support payments is in the larger percentile it affects efficiency positively. The study by Latruffe et al. (2017) does not show that the effects of CAP subsidies are unanimously positive for efficiency but differs country wise. They also show that the effects on the TE score are weaker the more productive a sample is.

Table 9: the most efficient farm in the sample

Output	4, 110,000
Area Utilized	138.70 ha
AWU	2.50
Intermediate Cost	1,850,000
FixedCost	3,710,000
LDI	0.18
Bought/Produced	36%
conventional	yes
Region south	yes
Age	61 yrs
Coupled support	900,336
Dept	55,690
TE- score	.93

As the results show some anomaly Table 9 was added as a discussion to illustrate the most efficient farm in the sample and show what the inputs look like on an efficient beef farm. As can be concluded the farm is medium sized compared to the whole sample, which further emphasizes no correlation between size and efficiency score. It can also be concluded that the farm has all the positive efficiency determinants, except for farm location in the south region. Also the most efficient farm show anomaly in the data, as its LDI is very low. This is another indicator that the sample selection has error, and that not all farms in the sample are specialized in beef. It could also mean that there is an error in the livestock variable.

Another important notice is that the technical efficiency score really is a comparison of the performance within that sample, which makes it difficult to draw solid conclusions by comparing it to other samples. A condition for estimating a TE- score is that all observations in the sample use the same technology. The difficulty in determining that fact both within the sample and compared to other samples makes all comparisons of results unreliable.

5. Conclusion

The aim of this master thesis was to assess the determinants of technical efficiency of Swedish beef farms, to establish a technical efficiency score of the given sample and to establish the relationship between organic/ conventional farming, age, farm size, location, support payments and level of technical efficiency.

A stochastic frontier Analysis was made based on a trans- log production function. In a second step of the analysis technical inefficiency was determined based on several determinants of inefficiency that were added to the model. A technical efficiency score could then be measured as the ratio between the stochastic frontier output and the observed output, establishing the technical efficiency score of 0.64.

Furthermore, the results show positive correlation between conventional farming, age, farm size, location in mid- Sweden, and coupled support payments over 90,000. The results also show a negative correlation between time and efficiency, indicting diminishing efficiency over the sample time period.

The distribution of the technical efficiency shows an anomaly that is not explained by the data, indicating a downward bias of the technical efficiency score. The likely explanation is that the sample selection is too broad and too generalizing over firms that have different production technologies.

This thesis acknowledges the environmental damages mitigated from beef production but argues for the need of a maintained Swedish beef production due to evidence found in the literature on its importance for other environmental and societal factors. The results show the presence of technical inefficiency within Swedish beef farming, which is why the policy recommendations made from the thesis results is to further understand the drivers of farm level technical efficiency and adopt policy measures that support efficiency- improving factors in order to maintain domestic production of meat and ensure a further step towards sustainable development.

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Appendix 1: Composition of input variables

Variable			Unit
Output Variable			
	FN2611	Beef cattle < 1yr old annual sales value	SEK
	FN2354	Fattening bulls 1-2 yr old annual sales value	SEK
Y= sales value meat and veal	FN2364	Heifers 1-2 yr old annual sales value	SEK
	FN2374	Fattening bulls > 2 yr old annual sales value	SEK
	FN2394	Heifers >2 yr old annual sales value	SEK
	FN2635	Other Beef cattle annual sales value	SEK
Input variables			
	FC0054	Operation manager and business owner	Hours
	FC0073	Spouse	Hours
	FC0076	Relative, regularly employed	Hours
X_1= Labour	FC0080	Hired manager	Hours
	FC0082	Regular employee	Hours
	FC0083	Employee by hour	hours
	FK1191	Permanent Grazing Land	Ha[3]
X_2= Area Utilized	FB0049	Other Grazing Land	Ha
	FK1161	Grass in crop rotation	Ha
	FD0231	Opening Balance Number of Beef cattle< 1yr old *0.4	LU[2]
	FD0101	Opening Balance Number of Fattening bulls 1-2 yrs old*0,7	LU
X_3= LDI[1]	FD0106	Opening Balance Number of Hefers 1-2 yrs old*0,7	LU
	FD0111	Opening Balance Number of Fattening bulls > 2yrs old*1	LU
	FD0121	Opening Balance Number of Heifers <2yrs old *0,8	LU
	FD0236	Opening Balance Number of Beef Cattle, other*0,8	LU
	FF0262	Fuel	SEK
	FF0279	Electricity	SEK

	FF0280	Heat	SEK
	FF0281	Water	SEK
	FF0260	Inventory rents and purchased services	SEK
X_4= Intermediate Costs	FF0261	Machinery service and reparation	SEK
	FF0264	Concentrates, bought	SEK
	FF0265	Roughage, bought	SEK
	FF0268	Fodder, own produced	SEK
	FF0282	Insurance	SEK
	FF0287	Building and land insurance	SEK
	FF0294	Veterinary costs	SEK
	FF0295	Other husbandry costs	SEK
	FF0278	Building maintenance	SEK
	FF0285	Rents	SEK
X_5= Fixed Costs	FF0288	Land tax	SEK
	FF0289	Interest	SEK
	FG0300	Depreciation buildings	SEK
	FG0365	Depreciation, machinery	SEK

[1]Livestock Density Units= LU/ha according to Kothman (1974)

[2] Livestock units (according to manevska tasevska et al (2013)

[3]hectares= Ares*0.1