THE IMPACT OF ANIMAL HEALTH ON TECHNICAL EFFICIENCY

EVIDENCE FROM SPANISH DAIRY FARMS

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The impact of animal health on technical efficiency

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Abstract

Dairy farms aim to increase milk productivity and efficiency, which puts extra demands on the cattle. Increased incidences of diseases, high treatment costs paired with poor animal welfare can be consequences. Therefore, this study investigates the impact of animal welfare on technical efficiency of Spanish dairy farms. A stochastic frontier analysis is applied to discover the effect of animal welfare indicators on a whole farm measure, namely technical efficiency. Three animal welfare indicators are specified as endogenous variables in the inefficiency equation of the Battese & Coelli (1995) model. The average technical efficiency is 90,6% and evidence is provided that farmers can benefit from increasing their size of the operation. Based on the obtained results it is concluded that a reduction of both, the calving interval and the somatic cell count will reduce technical inefficiency of Spanish dairy farms and improve animal welfare. Reducing the calving interval form 14.2 months (432 days) to the from literature proposed 12 months (or 13 months) will decrease technical inefficiency by 0.0298 percentage points (or respectively 0.0165 percentage points) and reduce the stress and reproductive problems of the cattle. Reducing the somatic cell count by 1,000 cells per millilitre decreases technical inefficiency with 0.000222 percentage points and reduces the risk for the cattle to become diseased with mastitis. The magnitude of this finding is small, but should be an incentive for Spanish dairy farmers to reduce their herd`s somatic cell count to avoid penalty fees from the European Union and become more efficient. In order to make more detailed inferences about animal welfare indicators, the used inefficiency equation could be modified by including additional variables and the integration of interaction terms.

Preface

In the following you are going to read my Master thesis that seeks to discover the effect of animal welfare on technical efficiency of Spanish dairy farms. At the start of this thesis I had neither expertise in the topic, nor in the method that I used in the analysis. Animal welfare was an abstract term and my knowledge about dairy cows was vague. Econometrics, was associated with mathematics, economics and according to fellow students a university course which was hard to pass. Throughout the thesis process, I became fond of animal science and discovered the possibilities of econometrics.

Nevertheless, I also faced several difficulties. The first weeks consisted of scanning the literature. I came across technical papers in dairy science journals about the metabolism of the cow, diseases and econometric papers consisting of more equations than words. Little information could be extracted while reading such papers for the first time. After a while however, I realized recurring technical terms in animal science and similarities in equations. Hence, it was challenging at the beginning, once I became familiar with the topic I got more inquisitive than before. However, learning to perform analysis with the statistic program STATA was the most demanding with respect to time and nerves. Searching through textbooks, YouTube videos, expert forums and the enormous STATA help file was one of the main tasks to come up with a simple code. Fortunately, I had great support from my supervisor, Xudong Rao, by which I escaped situations of despair and improved quickly. Thank you for the feedback sessions and being a tutor in econometrics and STATA.

Additionally, I would like to thank Alan Wall for providing me with the data set and his efforts to give an understanding to the data and context in several Email responses and a skype interview. Furthermore, I would like to express my gratitude to Henk Hogeveen. Our meetings gave me enlightenment about dairy cattle and crucial input for the animal welfare framework.

On a final note, I would like to thank my family for the support throughout my study, Laura for her critical input and creative ideas and Tarik for inspiring discussion about econometric related issues.

Content

1. Introduction

The first chapter provides the reader with background information about the dairy sector of the European Union and elaborates on the existing discrepancy between production increase and animal welfare. After the problem statement is described, the research objective and the research questions are provided, that aim at filling the revealed research gap.

1.1. Background

The European dairy sector has been experiencing a continuous milk production increase, which is displayed in figure 1. The annual average increase for the period between 2012 and 2017 was 2.7 million tons, with a downward sloping trend. The biggest increase in milk production is detected in two periods, 2013 to 2014 (5.1 million tons) and 2014 to 2015 (3.4 million tons). At this time the milk quotas for the European market were removed, resulting in the growth of the most productive dairy farms and the contraction of the less productive farms (Eurostat, 2016). Additional information on the abolishment of the milk quota is provided in Appendix 1.

The impact of the milk quota on European dairy farmers can also be seen in figure 2, which illustrates the historical raw milk prices of the EU-15 counties and Spain for the period of 2000 to 2017. The general trend for the Eu-15 shows an initial period of stable milk prices (30€/100 kilograms for 2000 to 2006) and two peak periods (2008 and 2014; with 35€/100 kilograms and 38€/100 kilograms, respectively) which are both accompanied by radical falls in the subsequent years. The first radical fall can be explained by the milk crisis in 2009 and the second fall occurred due to the abolishment of the milk quota in 2015.

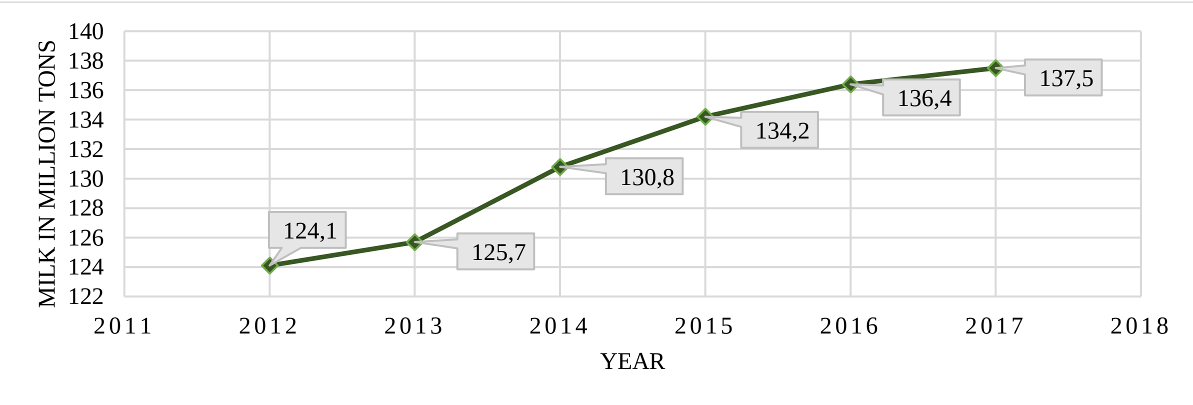

Figure 1 Raw milk prices, data source (Commission, 2017)

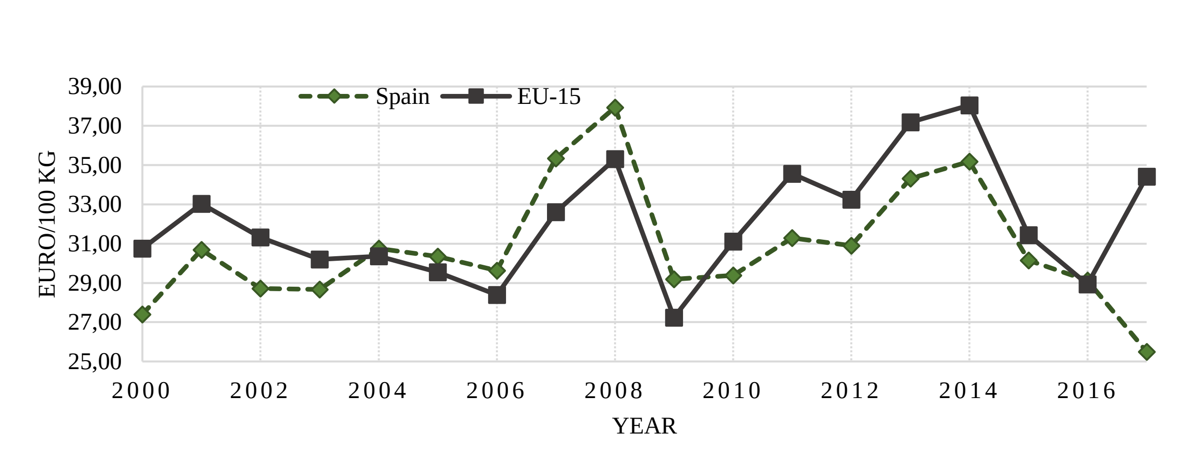

Figure 2 Milk production of the EU-15, data source (Commission, 2016)

After both crises a recovery phase is visible. As a response to the crises, the milk quota was increased annually and a soft landing program was introduced to this prevent negative trend. Spain, as part of the EU-15 experienced the same trends. However, according to data from the milk market observatory, Spain will profit to a lesser extent from the soft-landing recovery program as the EU-15 do. Consequently, falling prices tend to put revenue constraints on Spanish dairy farmers. From the input perspective, Spanish dairy farmers are pleased with low operating expenses compared to the EU-15 (evidence in appendix 2). However, prices for crucial input such as feed are likely to rise.

As a result, Spanish (and European) dairy farms have to cope with shrinking margins for raw milk production. This economic trend resulted in an increase in discontinuance of Spanish dairy farms and simultaneously an increase of average farm and herd size per in Spain and EU-15. Most remarkable, however, is the rapid increase in the productivity of dairy cattle. The productivity of dairy cattle, measured in milk yield per cow, for the EU-15 is displayed in figure 3. In accordance with Barkema et al. (2015) who argue that milk production per cow increases with 2 to 3 percent per year the data from the European Commission show the same, a steady upward trend. In 2003, the milk yield was 7.040 kilograms and increased yearly by about 140 kilograms, achieving a level of 7.625 kilograms in 2017.

Several scholars attribute the productivity increase to the rapid progress in genetics and management (Oltenacu & Broom, 2010; Barkema et al., 2015; Knaus, 2009; Broom, 2002). Such as the use of specialized dairy breeds (e.g. Holstein/Friesian), artificial insemination and nutritional diets with high-energy inputs.

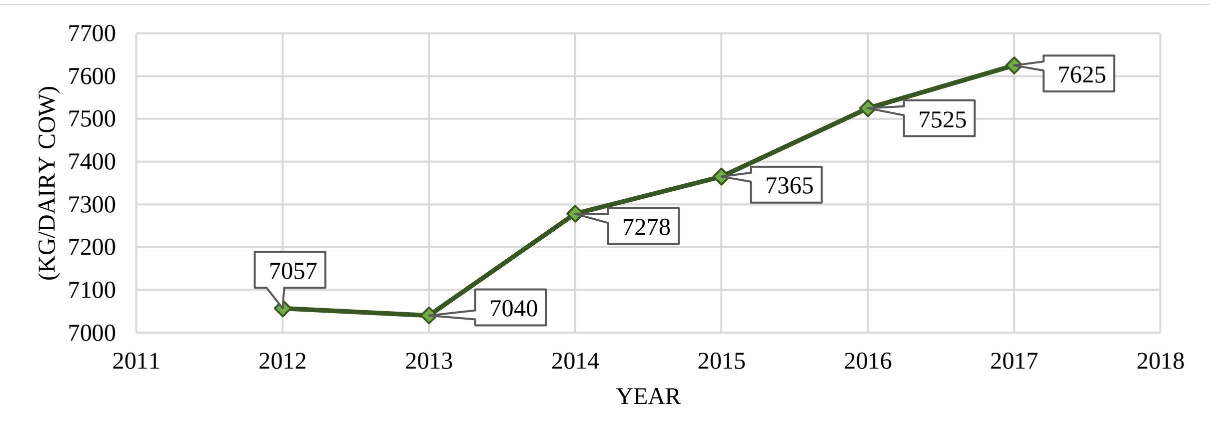

Figure 3 Milk yield per cow for EU- 15 (Commission, 2016b)

1.2. Problem statement

The introduction reveals that Spanish dairy farmers are exposed to economic pressure. Farmers relay more than ever on economic principles to overcome this situation and the effects are evident: production expansion, contraction of inputs and productivity increases.

Keyserlingk et al. (2009, p.4105) argued that the “increased production puts extra demands on the cow, [which is] likely leading to an increased incidence of disease”. Several scholars discovered that high yielding cows have a greater risk to become diseased with mastitis and lameness (Ingvartsen, 2003; de Haas, 2002; Van Dorp, 1998; Archer, 2010). According to Seegers (2003) mastitis appears to be the most frequent and most costly production disease in dairy and a clinical case of lameness (impaired locomotion because of e.g. foot lesion) is considered to be a painful condition and the main cause of infertility in dairy herds. Animal welfare awareness by the general public has increased, and especially visible indicators of poor animal welfare are of major interest for consumers, activists, and the media (Archer, 2010).

Consequently, dairy farmers have to cope not only with animal diseases and reproductive problems, but also with external concerns about animal welfare. Farmers who want to reduce animal diseases and reproductive problems experience increased management efforts and additional costs. Costs of poor fertility arise for example from additional inseminations, hormonal treatments, premature culling and extra veterinary and labour hours (Reinhard, 2000). For the case of mastitis, Halasa (2007) argues that besides others, treatment and control costs are high and financial loses occur due to penalties on infected milk and quantity loses. Consequently, it seems that actual animal wellbeing and external animal welfare concerns interrupt routine practices and force farmers to reallocate inputs within the farm.

Hence, animal welfare influences not only a partial area of the farm, like the milk yield or costs, but has an impact on the whole farm. In accordance with this claim, Barnes et al. (2011, p.2011) argued for “a whole-farm, rather than a partial indicator approach to assessing efficiency when noneconomic factors such as lameness are accounted for”. Therefore, farmers would be interested in the relationship between animal welfare indicators and a farm-level measurement, such as technical efficiency, to discover their influence on the whole farm productivity and evaluate the economic impact.

1.3. Study objectives

This study aims at clarifying if changing the animal welfare of dairy cattle will influence the technical efficiency of Spanish dairy farms. This study tries to bridge the gap in the literature between economic efficiency theories and animal welfare concerns, and will inform Spanish dairy farmers on their input usage, animal welfare, and their consequences on farm-level efficiency. To reach this objective the following research questions were formulated:

1) How are animal welfare indicators analysed in the field of economics?

2) Which economic efficiency theory can be used to analyse the data?

3) Which model and variables need to be selected?

4) What is the technical efficient of dairy farms in Spain?

5) To what extent do animal indicators effect the technical efficiency of Spanish dairy farms?

1.4. Thesis outline

This master thesis is structured as followed. After having introduced the issue at stake in the first chapter, the second chapter provides the reader with a preliminary literature review on the dairy cattle, animal welfare and technical efficiency analysis in agriculture. Chapter three entails the conceptual framework and the data analysis framework. Within this chapter, the dataset and method are discussed. The following chapter provides the empirical estimations and discusses the model choice. The fifth chapter presents and discusses the results of the analysis and ends with research limitations. The conclusion relates the main findings of this study to the research questions and suggests a direction for further research.

2. Literature review

The second chapter is a preliminary literature review and aims at answering research questions one and two. It introduces the reader to the life of dairy cattle and provides an animal welfare framework that displays how animal welfare can be measured in economic studies. Additionally, it elaborates on two well-established methods in technical efficiency analysis. Finally, the chapter gives an overview on studies that aim to discover the effect of animal welfare on farm level efficiency.

2.1. Lifespan of a dairy cow

In order to contextualize the research topic this section is dedicated to create a basic understanding of the life cycle of a dairy cow represented in figure 4. Since my study background is not in animal science this section will not be of technical manner, but rather supportive for a better understanding of the animal welfare framework and the discussion.

After the birth of a calf interventions, such as dehorning, vaccinations or the removal of extra teats take place and the calf is separated from the dam. In the so-called weaning period (between six to eight weeks), the calf gets used to a milk-free diet and prepared for the breading process. Sweeney et al. (2010, p.105) studied the weaning period of dairy cows and found that gradually weaning resulted in an increased starter intake and "prevented weight loss that occurred in abruptly weaned calves". Best results were found when the milk allowance was gradually reduced over a 10-day period.

In the breading period, the heifer (a female cow before it has calved) returns to the herd and is raised and prepared for the first gestation. The diet in this period is important for the development of the heifer. Butler (2000) researched the effect of nutrition on reproductive performance and concluded that, especially during the breeding period, protein rich diets support the milk production, but are also correlated to lower reproductive performance. Matthews (2011) explains the importance of accurate body score measures during the breeding period for control and management decisions.

After this period, at an age of 13 to 15 months, the heifer is mated with a bull or artificially inseminated. The pregnancy lasts for around nine months. The weaning and breading period as well as the gestation are influenced by management decisions. Consequently, the age of first calving can heavily vary. There is a vast amount of studies which relate the age of first calving to productivity (Pirlo et al., 2000; Nilforooshan & Edriss, 2004; Berry & Cromie, 2008; Haworth et al., 2008), reproductive performance (Ettema & Santos, 2004), health (Ettema & Santos, 2004), longevity (Gill & Allaire, 1976; Nilforooshan & Edriss, 2004; Berry & Cromie, 2008; Haworth et al., 2008) as well as economic performance (Gill & Allaire, 1976; Tozer & Heinrichs, 2001).

After the heifer calved, milk production starts and the cow is milked several times a day (mostly 1-3 times a day). A study by Österman & Bertilsson (2003) explains the effect of milking frequency on milk production. As it can be seen in the diagram below, the milk production reaches its peak in the first days after calving and declines afterwards.

The whole period during which a cow produces milk is called the calving interval. Similar to the age at first calving, the farmer can influence the length of the calving interval. Lehmann et al. (2016) discovered that cows with a high calving interval of 17 to 19 months produced significantly more than cows with a lower calving interval (less than 13 months). Controversy, Louca & Legates (1968) argue that the optimum calving interval for cows calving for the first time is 13 months (for second and later calvers 12 months). The general accepted calving interval according to Österman (2003) is indeed 12 to 13 months.

After the calving interval, the cow is dried off. This is a rest and regeneration period for the cow. With respect to milk production in the subsequent calving interval the recommended length of the dry period is more than 40 days (Coppock et al., 1974). Wildman et al. (1982) argued that a greater number of days open (days in which a cow does not give milk) is beneficial for the body score index, and hence for the regeneration and growth of the cow.

After the dry period, the cow will calve again and enter the lactation cycle for a second time. This cycle repeats itself until the dairy cow is culled or deceases.

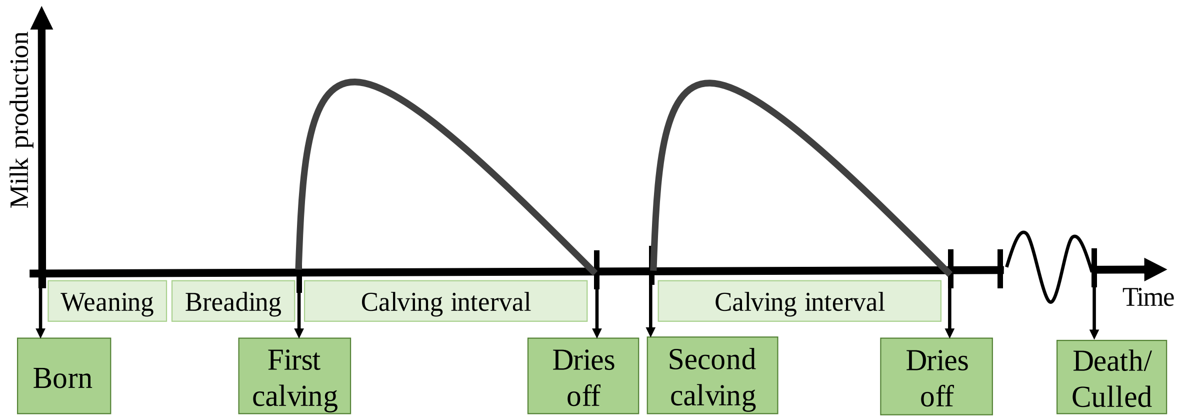

Figure 4 Lifespan of a cow

2.2. Animal welfare – From concept to indicator

Animal welfare definitions and the corresponding indicators to measure them are of vast existence in literature of various study fields. For this study, a specific conceptualization is required which contributes to the discovery of well-founded indicators useful for an economic analysis which also do not neglect wide-ranging social and ethical concerns. Allendorf & Wettemann (2015) underlined the necessity for animal-based welfare indicators in economic studies that better reflect the wellbeing of animals.

The framework[1] illustrated in figure 5 shows a conceptualization of the term animal welfare and provides an overview of dairy cattle indicators and how they are measured in an economic context. It consists of four levels, which compartmentalize gradually the generic term Animal Welfare (level one) into single indicators (level four). The first level of the animal welfare framework is based on Fraser (1997) and von Keyserlingk et al. (2009). The latter argued that animal welfare can be divided into three components; 1) Natural living, 2) Health and biological functioning, and 3) Affective state.

[1] The framework was created with the help of Henk Hogeveen, professor at the business economics chair group at Wageningen University.

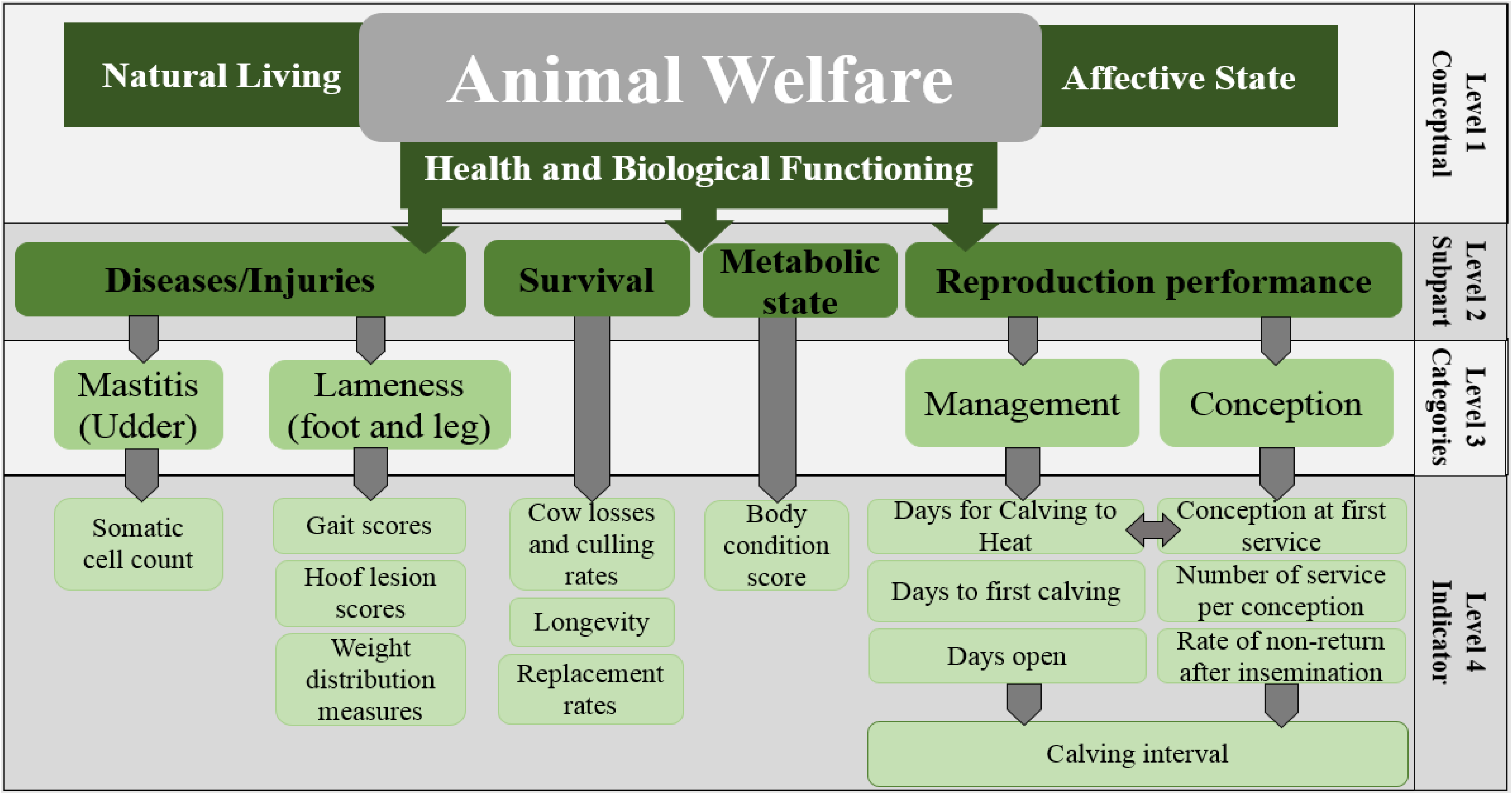

Figure 5 Animal welfare framework

Natural living explains the degree to which an animal is allowed to live a relatively natural life and express its natural behaviour. The debate among dairy scientists and the public comprises issues such as access to pasture and the cow-calf separation in modern housing systems (von Keyserlingk & Weary, 2007).

The affective state of the animal is a research area that draws much attention. The aim is to understand the mental state of the animals and discover measurements that give indications on not only pain or fear, but also the happiness of an animal. By this, management activities such as dehorning or tail docking can be analysed according to their effects on animal`s feeling.

"Health is an important part of welfare and whenever an animal is diseased, welfare is poorer than when there is no disease" (Broom, 2002, p.133)

Lastly, health and the biological functioning of the animal represent another component of animal welfare. This component includes the domains of impairments such as diseases and injuries, survival, metabolic state and reproductive performance. It contains the underlying logic that good animal health and proper biological functioning contribute to better animal welfare. This is also reflected by the statement of Broom (2002, p.133): "Health is an important part of welfare and whenever an animal is diseased, welfare is poorer than when there is no disease". Barkema et al. (2015) provided an elaborated discussion on the different components and argued that they can be seen as three distinctive, but overlapping perspectives on animal welfare. Management decisions taken in order to for example improve the natural living conditions for cattle can have influence on cattle`s health and biological functioning. Thus, for high animal welfare, the best management practices are those, which positively influence more than just one component.

The major interest of this study is animal`s health and biological functioning. Therefore, the following sections provide the reader with an insight on the four key components. The foundations of those components come from Pryce et al. (2004), Pryce et al. (1999) and the literature review by Rauw et al. (1998). A huge variety of cattle diseases and injuries exist. Broom (2002) analysis the effects of diseases on farm animal welfare and highlights that the major welfare problems for dairy cows result indeed from those two aspects, various leg disorders and mastitis. Therefore, the framework above focuses just on two impairments, namely mastitis and lameness.

Mastitis is an udder disease usually caused by infection and according to Seegers (2003) appears to be the most frequent disease in dairy herds. There is evidence that genetic selection for high yield increases the risk for mastitis (Van Dorp, 1998; Ingvartsen, 2003; Windig et al., 2005). As represented in the fourth level of the framework, a good indicator and routine measure to detect mastitis incidences is the somatic cell count (SCC; Windig et al., 2005). Kehrli and Shuster (1994) relate the SCC to the presence of inflammation in infected mammary glands and reduced milk quality.

Lameness is a foot or leg disease described by Archer (2010, p.2) as "impaired locomotion, regardless of [the] cause". It is often associated with painful foot lesion and hind limb problems. Special devotion is assigned to this impairment, because the impact on the individual animal is clearly visible and perceived from the general public as an indicator for poor animal welfare. Lameness is detected by conducting mobility scores, which are an objective measurement to analyse the gait of the cattle. The score is based on the work of Whay et al. (1997) and used by, for example, Reader et al. (2011) to quantify the effects of mobility on milk yield. Hoof lesion scores and weight distribution measures are other objective measurements.

Survival represents the second category and entails replacement and death and culling rates, as well as information on the age and longevity of the herd. Through those measures, inferences on the average

age of the cattle and farm performance can be made. High culling rates for example can be an indication of cattle health problems, physical defects or low production (de Mello, 2004).

The metabolic state represents the third category of level two and provides an overview on the cattle's stage of life. Body condition scores (BCS) reflect the state of the animal indicating whether the animal`s growth occurs in an expected and desired way. It is a control measurement and, in case of deviations, management action can be taken. Gallo (1996) discovered in their study the effect of different BCS on milk yield.

Reproductive performance reflects the fertility of dairy cattle and is defined as "the ability to conceive and produce a viable calf following an appropriately timed insemination" (Royal, 2000, p.487). As it was presented in the introduction, poor fertility is not only associated with high economic costs but is accompanied by animal welfare implications. In discussion with an expert[2], the framework subdivides reproductive performance into two categories, management and conception.

The management category entails indicators, which can actively be influenced by the farmer. The age at first calving, which is defined as the period the cow needs to reach maturity, is an example for management intervention. According to Hare (2006) the age of first calving can be adjusted in order to achieve better economic results. Pirlo et al. (2000) discovered a positive effect of age at first calving on milk yield and that cows which calve for the first time at 23 to 24 months appear to be most profitable.

The conception category entails measures, which reflect the intrinsic conception capacity of the cattle and are argued to be beyond the control of the farmer. González-Recio (2004) used the number of inseminations per cow as a direct measurement of conception ability. However, successful insemination is not only dependent on the cattle itself, but also on the managerial capability. Timing the insemination and controlling for outer conditions may influence the success rate likewise. Also the quality of the data recordings may vary, which according to Pryce et al. (2004) results in an insecure measure which needs to be used with caution.

The characteristics and intensity of both categories together are correlated with the calving interval, which can be seen as an overall measure of fertility. The calving interval is defined as the interval between two subsequent calving's. Studies by Arbel et al. (2001) and Lehmann et al. (2016) used the calving interval as a sole indicator for fertility and applied it in order to discover the effect on production and profitability of high yielding cows.

2.3. Efficiency analysis in dairy farming

The introduction elucidates the need for an economic analysis of the technical efficiency of Spanish dairy farms and simultaneously allows estimating the impact of animal welfare indicators on technical efficiency. In technical efficiency analysis, there are two well-established methods: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The former is a non-parametric approach which uses mathematical programming techniques and originates from the work of Farrell (1957) and Charnes et al. (1978). The latter is a parametric approach used by econometricians and originates from the work of Aigner et al. (1977) and Meeusen & van Den Broeck (1977). The subsequent paragraphs highlight that both methods are based on the same economic concept, but differ in their estimation execution.

In general, technical efficiency in agriculture can be used to benchmark farms and give an indication on farmers' ability of how efficiently production inputs are being transformed into outputs. Bogetoft et al. (2006, p.459) defined technical efficiency as "producing the most outputs from a bundle of inputs or conversely using the least inputs to produce a given bundle of outputs [...]" and indicated thereby that

[2] Henk Hogeveen, professor at the business economics chair group at Wageningen University

two perspectives exist, the output-related perspective and the input-related perspective. If an input oriented perspective is used, researchers can "identify technical inefficiency as a proportional reduction in input usage, with output levels held constant" (Coelli et al., 2005, 180). Technical efficiency is a relative measure that indicates the relationship between an individual farm to the farms with the best practice (also called the peer). The distance to this efficiency frontier gives an indication about the level of inefficiency of this individual farm.

To benchmark farms using the SFA, production, cost and profit functions can be estimated, which act as the boundary representing the best possible allocation (Coelli, 1995). In the following, production frontier models are considered. In SFA, a stochastic production frontier is used and consists of a function of inputs with assigned parameters and a composite error term. The error term is further separated into two components, a standard noise term and a non-negative term reflecting technical inefficiency (Cuesta, 2000). Kumbhakar & Heshmati (1995) and Cuesta (2000) provided evidence of how the SFA measures technical efficiency of dairy farms in Sweden and Spain, respectively. Both included panel data in their stochastic frontier model (1976-1988 and 1987-1991) and concluded that the technical efficiency of dairy farmers is on average 85% and 83%.

In the DEA method, the level of inefficiency is estimated based on a distance measure between an individual farm and the frontier. The results are interpreted as efficiency scores, which range from zero to one, with high values indicating a small distance to the production frontier and hence a high efficiency. Input variables are used to construct the economic frontier. Johansson (2005) and Kapelko (2013) used panel data for dairy farms in Sweden (1998-2002) and Spain (2001-2009), respectively. The two studies found that technical efficiency was on average 77% and 72%. All of the above-mentioned studies included either income from milk or milk production as the output variables. The selection of input variables varied, whereas labour, land, the number of cows, forage and animal expenses were included in all of the studies in some form. The following paragraphs elaborate on the methods used and provides the reader with an extension of the models.

Further, there is a growing interest in agriculture related studies to include other explanatory factors that might influence technical efficiency. In order to do so, the DEA method is often used in combination with a regression model in the second stage to analyses the efficiency of farms and make an estimation on those explanatory variables. This procedure is called a two-stage approach. The first stage is comprised of data envelopment analysis to analyse the technical efficiency of the farms. The second stage consists of a regression analysis which quantifies the effects of the explanatory variables, such as animal health indicators or operational management indicators, on technical efficiency. The regression results indicate marginal effect of each of the explanatory variables on technical efficiency. Literature applies and discusses the suitability of a Tobit regression or Logistic regression in combination with DEA (Afonso, 2006; Allendorf & Wettemann, 2015; Hansson et al., 2011).

Hansson & Öhlmér (2008) and Allendorf & Wettemann (2015) use this approach to investigate the impact of operational management on dairy farm efficiency and the effect of animal welfare on technical efficiency of German dairy farms, respectively. Also, Hansson et al. (2011) and Barnes et al. (2011) used DEA in the dairy sector to discover the effect of a cattle disease (mastitis and lameness, respectively) on technical efficiency.

To characterise the determinants of inefficiency using the SFA method, researchers need to further specify the inefficiency-related error term in the composite error term. Common practice is to assume the inefficiency-related error term to follow the truncated normal distribution with the mean of the pre-truncated normal distribution determined by a group of explanatory variables related to inefficiency. According to Belotti (2012), the main interest of researcher using this method is to make inference on both the frontier parameters and the inefficiency function. The advantage of the model is the inclusion of exogenous variables that are considered to have an influence on the inefficiency term. Kumbhakar et al. (1991) and Cuesta (2000) applied a stochastic frontier model to the dairy sector in the United States and Spain, respectively. Lawson et al. (2004a) used a stochastic frontier model to explain the relationship between dairy cattle disorders and the technical efficiency of Danish dairy farms.

2.4. Animal welfare indicators and technical efficiency – The dairy sector

The introduction indicates that the scientific literature provides a vast range of studies analysing the relationship between animal welfare and economic measures. However, as it can be seen in the literature review by Pryce et al. (1999) and Ingvartsen (2003), a huge share of those studies provide evidence on the impact of animal welfare and management practices on a partial measurement such as milk yield or additional costs. The integration of a whole farm measurement like technical efficiency is rarely done. Exceptions are Allendorf & Wettemann (2015), Barnes et al. (2011), Hansson et al. (2011), Lawson et al. (2004a) and Lawson et al. (2004b). All of them use either the two-stage approach or the SFA described above, to analyse animal welfare indicators and their relationship with technical efficiency of dairy farms. A summary of their results is presented in the subsequent paragraphs.

Lawson et al. (2004a) expected that a lower cattle health, reduces milk output or the efficiency of inputs. They found evidence that there is indeed a negative effect between incidences of milk fever and technical efficiency. However, for lameness, ketosis and digestive disorders a positive effect on technical efficiency was discovered. Additionally, Allendorf & Wettemann (2015) found that a up to a somatic cell count of 160,000 cells per millilitre, an increase in somatic cell count will increase inefficiency. Unexpectedly, after this threshold, an increase in the somatic cell count will decrease inefficiency. With respect to lameness, Barnes et al. (2011) found that farms with low rates of lameness have a higher technical efficiency than farms with a high rate of lameness.

The study of Lawson et al. (2004b) concluded on the basis of Danish dairy farms that there is no negative relationship between reproductive disorders and milk production efficiency. However, evidence was found that fertility indicators influence the technical efficiency. Both Lawson et al. (2004a) and Allendorf & Wettemann (2015) observed that a longer calving interval has a negative effect on the technical efficiency, whereas a lower cow age at first calving has a positive effect on the technical efficiency in Danish and German dairy herds.

Furthermore, a high percentage of cow losses and a high replacement rate have a negative effect on technical efficiency (Allendorf & Wettemann, 2015). The latter, however, is dissented by Lawson et al. (2004a) who found the contrary, stating that efficient farms have high replacement rates.

Finally, Hansson et al. (2011) analysed preventive management efforts in the context of mastitis incidences. They found that loose housing systems and specific practices during the milking process increase the probability of a farm being fully efficient.

3. Conceptual framework and methodology

The third chapter provides the reader with a conceptual framework and a data analysis framework. Within the data analysis framework an elaboration is made on the first, the dataset, second, the approach and finally, on the stochastic frontier analysis. This chapter is structured in a way that it starts with a generic overview and gradually specifies the approach. This chapter contributes to answer the third research question.

3.1. Conceptual framework

The conceptual framework is shown in figure 6. As it is illustrated, the study is divided into three phases, which provide the sequential guideline for this research project and are established to answer the five research questions provided in the introduction. The first phase is comprised of the literature review in the second section. Based on the literature review, research questions one and two can be answered. Phase two consists of the search and selection of a suitable model and variables. It will provide the reasoning and answers to research questions three. Finally, phase three presents the results and the discussion. It will highlight the technical efficiency of Spanish dairy farms and evaluate the effect of animal welfare indicators on technical efficiency. Existing studies and findings will be used to compare and critically reflect on the results. Furthermore, limitation, especially with respect to data and the model selection, will be revealed and implications for policy and further research will be provided. Altogether, phase three will provide information for answering answer research questions four and five.

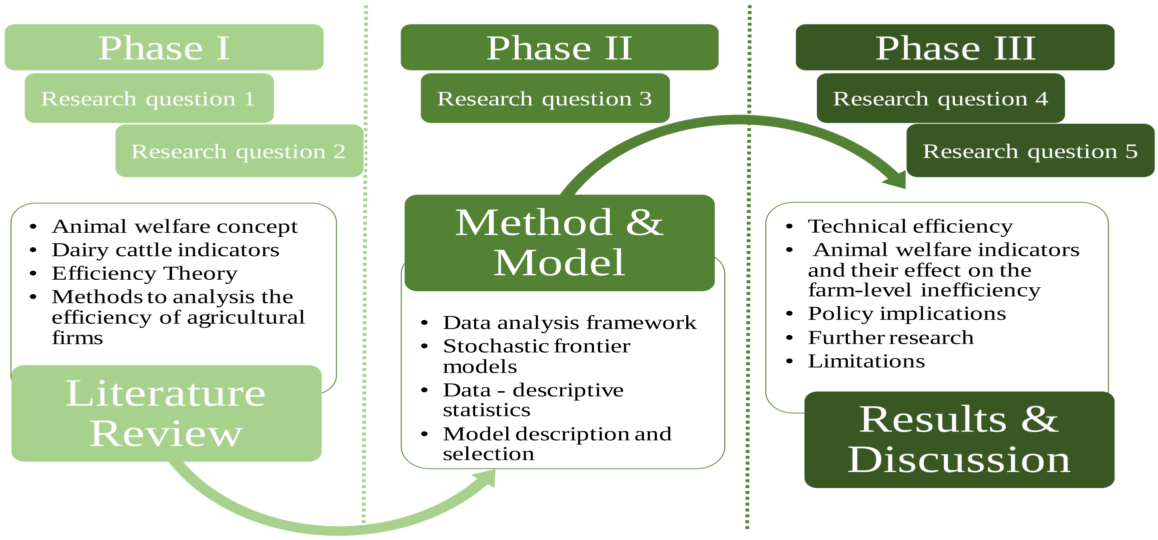

Figure 6 Conceptual framework

3.2. Data analysis framework

3.2.1. Data

The data used for this master thesis project was provided on agreement by Alan Wall, an associate professor in the department of economics at the University of Oviedo, Spain. The data represents dairy farms in the region of Asturias, Spain, and can be classified by the following two categories, accountancy data of Spanish dairy farms and animal indicators. The former, is generated by an extension program of the regional government and covers the period of 2006 to 2014. The panel data is unbalanced, which will be evaluated more in detail in the data analysis chapter. The data used in this project is a subset of this dataset and includes in total 1160 observation of 197 different farms, which are simultaneously members of the same breeding cooperation. The breeding cooperation provided the second part of the data, the animal indicators, for each of the dairy farms. They measured a variety of indicators reflecting the animal health, fertility and characteristics of the dairy cattle.

Figure 7 displays the entire data set that is used for this research. It can be seen that the input variables labour (X1), forage production expenses (X2) and animal expenses (X6) are aggregated measures. The arising variables (e.g. X6.1.) of a disaggregation of those inputs could be used in the analysis. However, the aggregation was conducted by Alan Wall in order to generate a solid measure and avoid variables with missing values.

Finally, it is to mention, that there is an extension to this data in progress. It will contain measurements on cow comfort like for example the access to pasture or the flooring of the barn. Conceptually, it would fit in the animal welfare framework of chapter three under the affective state.

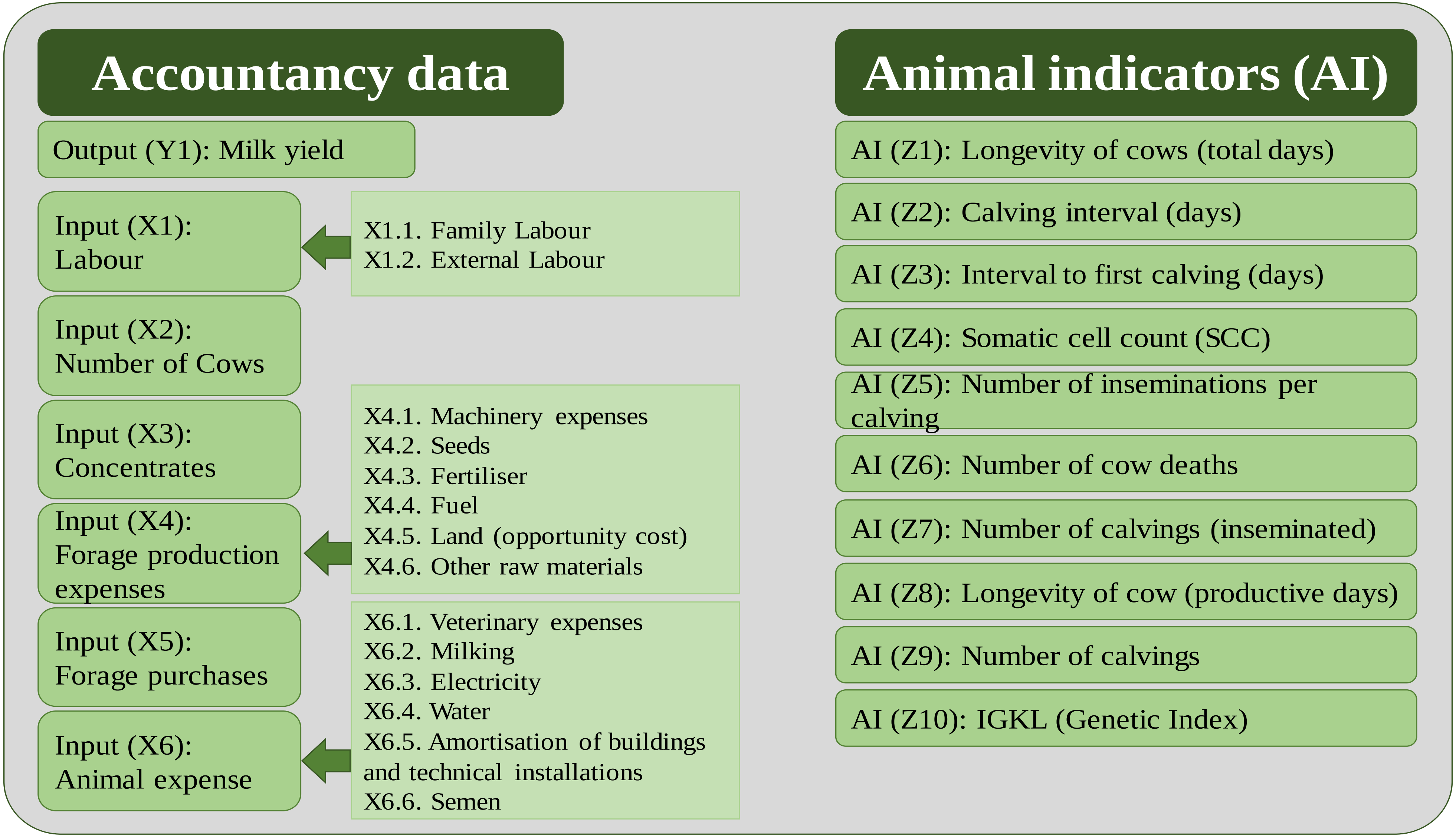

Figure 7 Dataset for analysis

3.2.2. Approach

As presented in the literature review, the two-stage DEA approach and the stochastic frontier analysis are both applicable in an agricultural economic context. For this research, the stochastic frontier analysis is used. The approach is displayed in form of a data analysis framework in figure 8 and the reasoning with respect to the method choice is elaborated in the following section.

The econometric model consists of two equations, the production function and the inefficiency equation, which are solved simultaneously using the maximum likelihood method. The accountancy data is used in order to construct the production frontier, by using the output milk yield (Y1) as dependent variable and the inputs (X1-X6) as independent variables. As a result, parameter estimates for each of the six inputs and technical efficiency scores will be generated. The aim is to make inferences on average technical efficiency of dairy farms, the importance of the different inputs, as well as to discover a possible time trend in technical efficiency.

Moreover, based on the parameter estimates an indication on the returns to scale can be derived, which will provide information on whether the farms are operating at an optimal scale.

The inefficiency equation will include exogenous variables, denoted with Zi, which are expected to have an effect on inefficiency. Under consideration of the animal welfare framework and an expert discussion[3], a combination of the following five animal indicators will be integrated in the inefficiency equation: *Longevity, Interval to first calving, Somatic cell count, Calving interval* and *Number of inseminations per calving*. Next to the animal indicators, a time component and a genetic indicator will be included to control for technological change during the period and difference in genetics, respectively. Parameter estimates for the animal indicators and control factors will show their effect on inefficiency in form of significance and direction. Furthermore, marginal effect calculations provide insight on the effect of an incremental in- or decrease on technical inefficiency.

The choice for stochastic frontier analysis over the two-stage approach is motivated by technical and personal reasons.

Technically, the main advantage of the SFA is that it allows the inclusion of measurements errors or statistical noise (Scippacercola & D'Ambra, 2014). Firms can deviate from the production frontier not only because of technical inefficiency, but also due to measurement errors or statistical noise. The DEA is more sensitive to extreme observations, because deviations from the production frontier mainly account for inefficiency. Additionally, the computation of the parameter estimations of the exogenous variables and the production frontier variables occurs simultaneously. In the two-stage approach, however, the inclusion of exogenous variables has been recognized as biased (Wang & Schmidt, 2002). Nevertheless, there is a vast amount of studies which aim to create methods to reduce this bias and make valid inferences with the two-stage method. Simar & Wilson (2007) provide a good overview about the topic and advocate for the use of a single and double bootstrap procedure.

From a personal perspective, the choice for the SFA is made, because Wageningen University provided the access to the computer program STATA, which is a suitable tool for stochastic frontier analysis. Additionally, the synergy between personal development in the field of econometrics, which fell short in my study program, and expert support in the method and computer program, were motivation to use the stochastic frontier analysis

[3] Henk Hogeveen, professor at the business economics chair group at Wageningen University

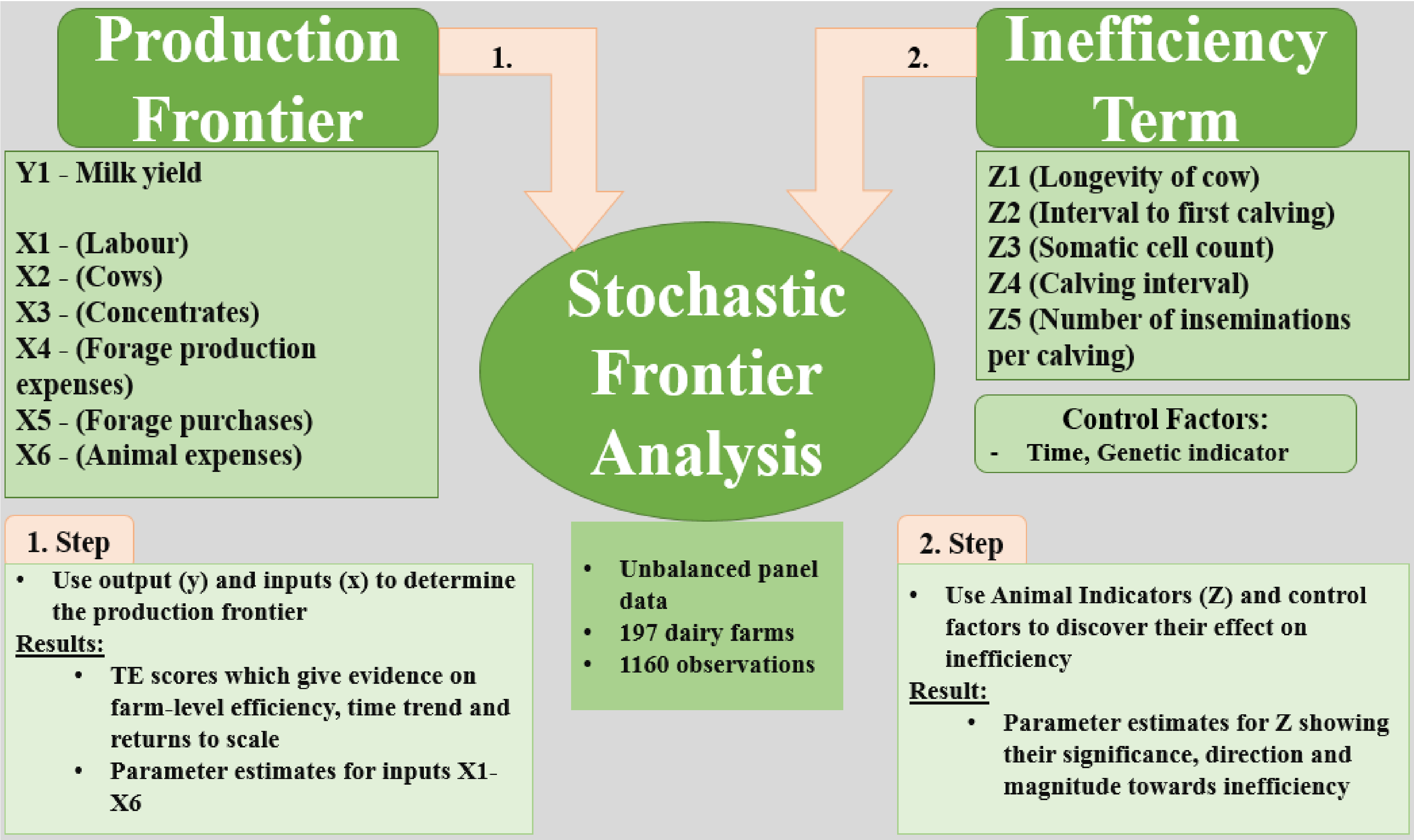

Figure 8 Data analysis framework

3.3. Stochastic frontier model

Production theory states that "If actual output, given inputs, falls short of the maximum possible output level, then the production will not be on the frontier" (Kumbhakar et al., 2015, p.12). In other words, a firm that cannot utilize its inputs as good as the best performing firm in order to produce a given set of outputs, is according to production economics technical inefficient.

To benchmark firms, a production frontier with an underlying functional form is created. An overview about different functional forms in the context of stochastic frontier analysis can be found in Kumbhakar et al. (2015). For this research, the Cobb-Douglas (CD) production function and the translog production function were taken into consideration. As it can be seen in the formulas[4], both production functions are similar in the sense that they include the outputs and inputs in a logarithmic form. The translog function can be seen as the more general version of the CD since it additionally includes interaction terms of the inputs. Cuesta (2000) applied the translog production function in the context of Spanish dairy farms. He included interaction terms of inputs and added a dummy variable to control for neutral technical change. In this research, the utilization of the CD function in the final model resulted in significant estimates. The use of the translog functional form resulted in the model to converge for estimation but only if no exogenous variables were included in the inefficiency term. Since the inclusion of exogenous variables is of mayor importance for the objective of this research, the CD functional form was chosen for the production frontier.

The level of inefficiency is dependent on the firm's distance to the production frontier. With respect to the production frontier models, there is a distinction between distribution free models and parametric models. According to Sampaio (2013), if the former model is used, the researcher cannot distinguish the inefficiency effect from the statistical error. The latter uses two random variables denoted with u_i and v_i, and allows to estimate the inefficiency effect and statically error separately. For this thesis, the choice is made to use a parametric model.

According to Kumbhakar et al. (2015), the general accepted distribution for the statistical error (v_i) in a parametric model is a zero mean normal distribution. For the inefficiency distribution (u_i), despite the existence of many other distributions, a truncated normal distribution is chosen to specify and estimate the inefficiency effects of chosen explanatory variables. Compared for example to the half-normal distribution, the truncated normal distribution is more flexible. It can have a nonzero mode, allowing the "peak" of the distribution to vary on the x-axis (entails the technical inefficiency scores ranging from zero to one). Figure 9 shows density plots of truncated normal distributions for different means (μ) and variances (σ^2). It illustrates the distribution`s flexibility as well as the capacity of the mean to shift.

[4] The Cobb-Douglas production function is given by: $lny = \beta_0 + \sum_j \beta_j lnx_j$.The translog production function is given by: $lny = \beta_0 + \sum_j \beta_j lnx_j + \frac{1}{2} * \sum_j \sum_k \beta_{jk} lnx_j lnx_k$

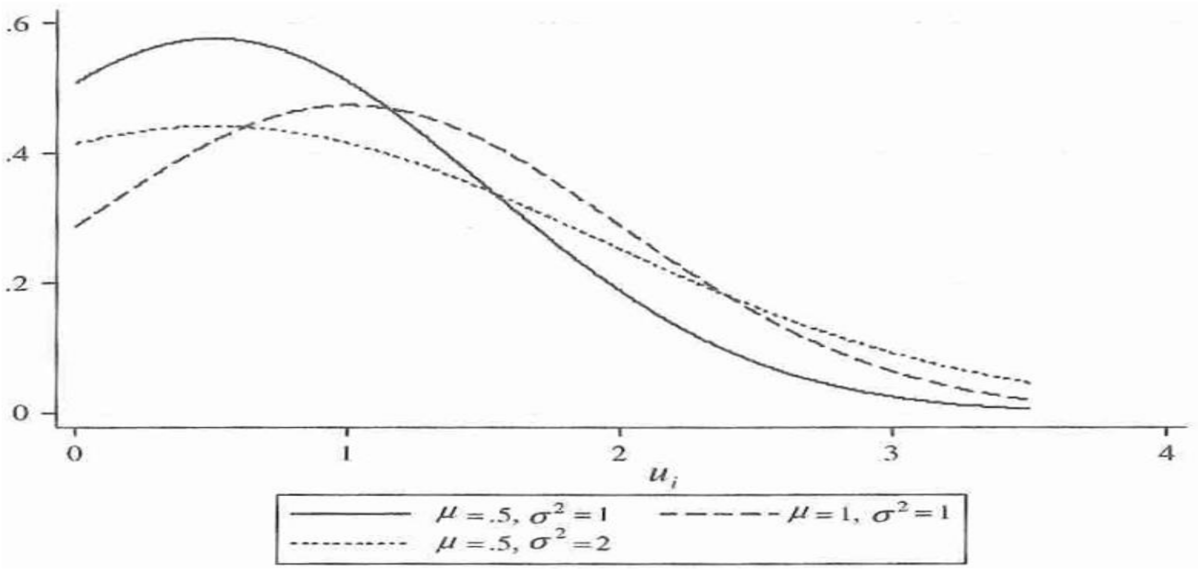

Figure 9 Density plots of truncated normal distribution (Kumbhakar et al., 2015)

The inefficiency equation is given in section 4.2. There are two measures of the unconditional mean of μ_i. According to Kumbhakar et al. (2015) the unconditional mean of μ_i calculates a point estimate of μ_i, under consideration of the given ϵ_i. Contrary to the conditional mean of μ_i, which just gives an overall average technical efficiency score, the unconditional mean of μ_i determines the technical efficiency for each observation. STATA provides two estimates of technical efficiency, namely the JLMS and the BC. Both originated in the work of Jondrow et al. (1982). They estimate μ_i from the expected value of μ_i and under consideration of the composed error term of the model, $\epsilon_i = \vartheta_i - \mu_i$. The two estimators differ slightly in their formulas[5], but the derived estimates are usually very similar. By sorting the technical efficiency scores by year, we can compute an average value of technical efficiency per year and display a potential time trend.

Since the objective of the research is to discover if there is an effect of animal welfare indicators on technical inefficiency, the model needs to fulfil the requirement of including exogenous variables in the inefficiency term. Besides others, the two papers of Kumbhakar et al. (1991) and Battese & Coelli (1995) introduced the inclusion of exogenous variables in the inefficiency term. The former included the farmer`s education and the operational size in the inefficiency equation while analysing U.S. dairy farms. The latter, included demographic characteristics and a time component in the ineffícacy equation in a panel data study in the context of Indian paddy farmers. Both also allowed the variance of the inefficiency term to be a function of the Z variables (called inefficiency explanatory variables). For this research the Battese & Coelli (1995) model is chosen, since it allows the inclusion of exogenous variables, is applied to panel data and is compatible with the STATA command *sfpanel*.

Similar to the discussion of the translog functional form in the production frontier above, an additional effort was made to include interaction terms of input and exogenous variables in the inefficiency equation. By this means, it was desired to make a more detailed inference about the origin of inefficiency. Huang & Liu (1994) developed a model in which the exogenous variables (Z`s) and the interaction term of inputs and Z variables are included in the inefficiency equation. Lawson et al. (2004a) based their model with a translog functional form on the work of Huang & Liu (1994). They explain the

[5]The JLMS produces estimates of technical efficient via: exp[-E($\mu_i|\epsilon_i$)]. The BC produces estimates of technical efficiency via: E(exp(-μ_i.)| ϵ_i).

effect of animal health on inefficiency in the context of Danish dairy farms. Besides demographic characteristics and genetic indicators they, also used the cross product of four cattle diseases and six inputs as interaction terms.

Within this research, the attempt was made to include interaction terms of the somatic cell count and the six input variables. By this means, an inference could have been made on how the disease constraints the productivity of the individual inputs. Several models similar to Huang & Liu (1994) and Lawson et al. (2004a) were constructed but failed to converge for the estimation. Due to time constraints and possible data problems this attempt was stopped and the focus was redirected to the Battese & Coelli (1995) model without interaction terms.

4. Empirical estimation

This chapter elaborates on a dataset of Spanish dairy farms and discusses the model choice. A first impression on the sample data is given by summary statistics and contextualization of the empirical data. Afterwards, the stochastic frontier model is specified and the integration of animal welfare indicators is discussed.

4.1. Descriptive statistics

The data set shows unbalanced panel data for the period of 2006 to 2014. In total, it contains 197 different farms and nine consecutive years. With respect to the T_i *distribution*[6], 15 percent of the farms provided observations for all nine years. Additionally, 50% of the farms have at least observations for six years. Figure 10 illustrates the observations per year. It is noticeable, that in year 2014 fewer (88) observations were conducted, than on average in the years before (134). Throughout this section, mean measures are used to analyse the data. In few instances, median measures are taken to spot and examine unusual deviations.

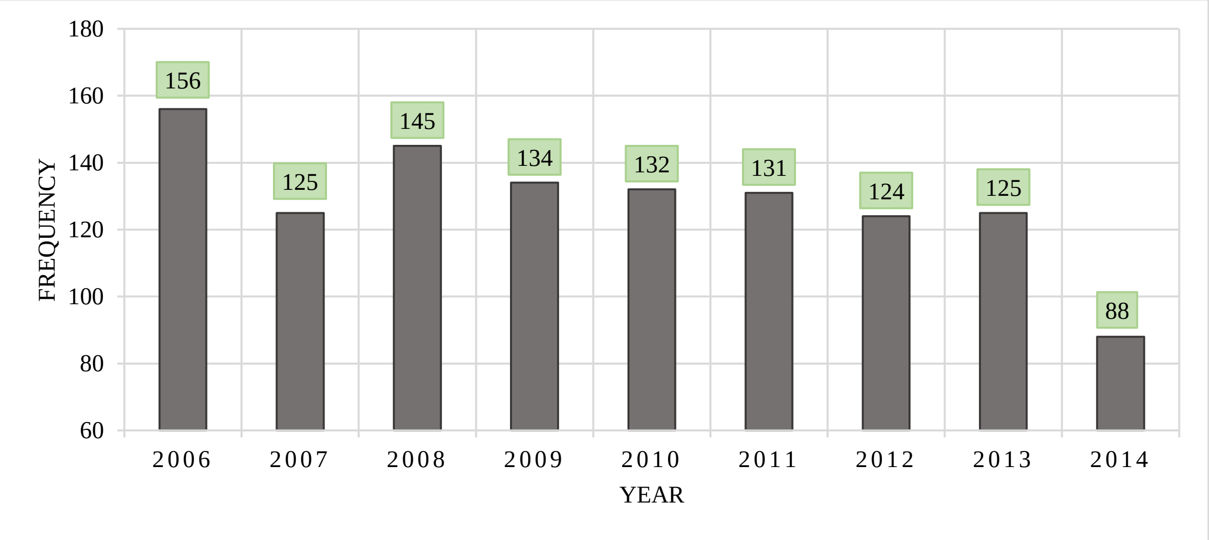

Figure 9 Observations over time

Table 1 below displays the summary statistics of the variables that are included in the production frontier and the inefficiency equation. In general, each variable is indicated by a label, the mean value, the standard deviation, and the minimum and maximum values. With respect to observations, it is noticeable, that all variables provide data points for all observations (1060), except for the indicator *Longevity*, which shows 76 missing values.

[6] The STATA command *xtset* provides the T_i *distribution* that gives information on how balanced the dataset is.

Table 1 Summary statistics

Variable	Label	Mean	Std. Dev.	Minimum	Maximum
Production Frontier					
Milk (litres)	Y1	467,177.7	348,302.7	74,956	3,548,764
Labour (euros)	X1	5,512.033	3,428.154	1,513.357	54,413.25
Cows (heads)	X2	55.512	34.599	11	324.5
Concentrate feed (kg)	X3	211,075.5	157,937.1	5,770	1,426,382
Forage production (euros)	X4	32,674.67	25,502.24	3,061.294	205,642.5
Forage purchase (euros)	X5	11,087.78	15,663.93	11.544	180,556.8
Animal expenses (euros)	X6	22,817.21	18,452.19	1,638.632	230,937
Inefficiency Equation					
Calving interval (days)	Z1	431.614	26.719	370.417	540.619
Interval to first calving (days)	Z2	821.441	72.181	662.5	1,290.25
Somatic cell count (SCC)	Z3	295.051	121.401	64	775.546
Longevity (days)	Z4	2,162.214	407.935	751	4,147.167
Genetic Indicator (IGKL)	Z5	8,076.821	221.1776	7,313	8,660
Insemination per calving (#)	Z6	2.259	0.442	1.234	4.613

The output variable *Milk* accounts for the yearly milk production in litres per farm. The average milk production per farm is 467,178 litres. Judging from the standard deviation, a huge variation among the farms exists. The most productive farm (3,548,764 litres) provided 47 times more milk per year than the lowest productive farm (74,956 litres).

Labour is measured in euros and represents the farm`s social security expenditure on hired labour and family labour. It is expected to give a more reliable indicator than estimates of full-time and part-time equivalents. On average Spanish farms spent 5,512 Euros on social security per year representing their average labour effort.

The number of *cows* is an indication for the size of the farm. The average farm`s herd size is 56 cows, whereas the biggest farm has 325 cows and the smallest 11. To discover the productivity of the cattle in the sample, the milk per cow ratio is calculated and displayed in figure 11. The productivity of dairy cattle in the sample period from 2006 to 2014 is on average 8,416 litres per cow per year.

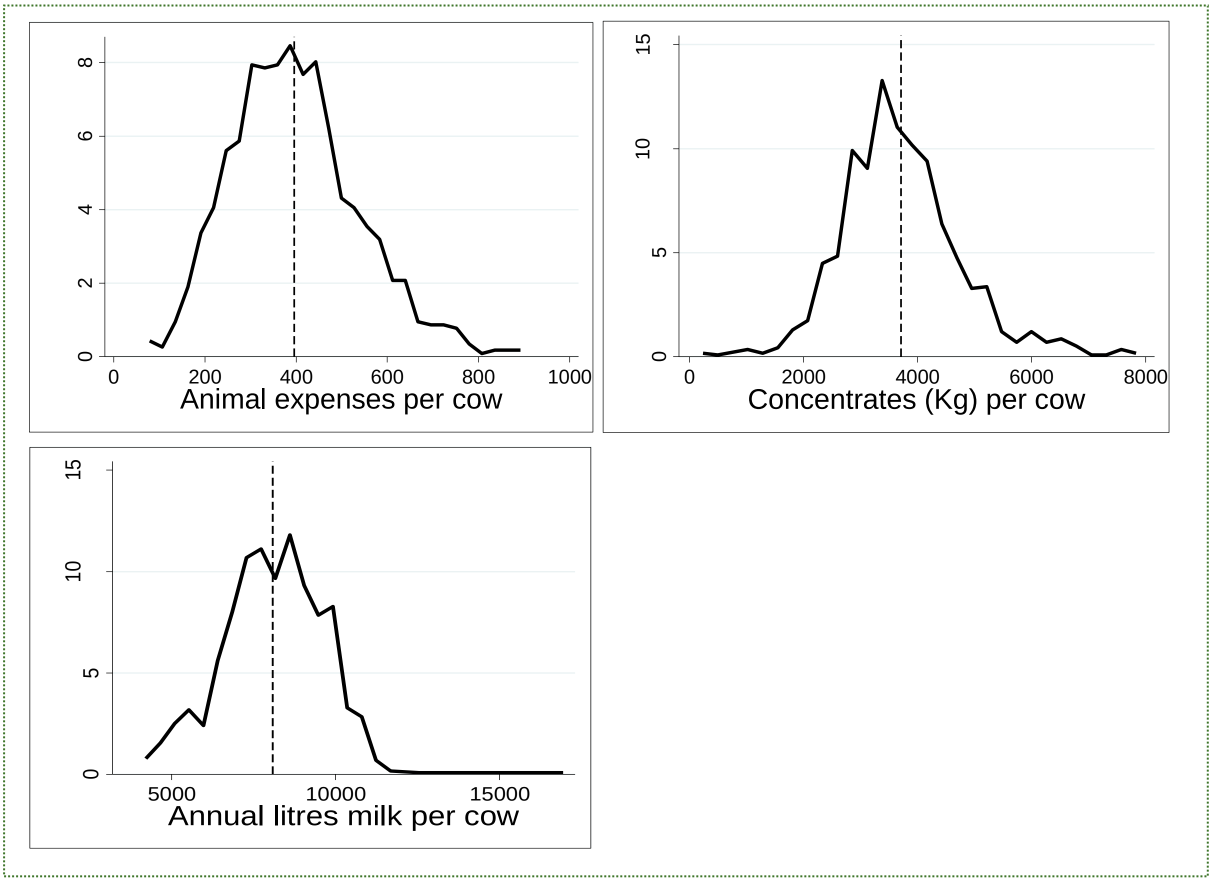

Figure 10 Three productivity ratios

Figure 12 indicates the time trend of dairy cattle`s productivity measured by the use of the mean and the median. In anticipation of positive outliers that shift the mean measure to the right, the 50% percentile (median) is displayed to prevent misinterpretation. In general, the period 2006 to 2013 shows a stable productivity measured by the use of the mean (median) at a range between 8,135 (7,881) litres and 8,603 (8,218) litres per cow per year. The upward trend starting from the year of 2014 with a mean value of 9,169 was expected to be caused by outliers. However, the median measure underlines this trend, indicating that the positive outliers do not influence the mean values in a strong manner.

Concentrate feed is measured in kilograms per year. Besides the normal forage, an individual concentrate mix is supplied to the cattle, containing high amounts of energy and important nutrients such as and proteins. On average, a farmer provided 211,076 kilograms of concentrates on his farm. The concentrate to cow ratio is an indication of how intensive the production is. Figure 11 shows that on average 3,710 kilograms of concentrates are supplied per cow. However, it has to be taken into account that this measure is related to the quantity and neglects information on the type and quality of the concentrates.

Forage production expenses as well as *forage purchases* are measured in euros and together present the basic source of feed for the cattle. The former, accounts for on average 32,675 euros per farm per year. The latter indicates that on average 11,088 euros are spend to purchase forage. Combining both measurements shows that three times more money is spent on growing own forage compared to external forages purchases. However, no information is provided on the quantities produced or purchased.

The last input variable, *animal expenses*, includes costs for the veterinary, buildings, semen and other inputs such as water, electricity and milking. On average, a farm has 22,817 euros of expenses per year.

The animal expenses to cow ratio is represented in figure 11 and shows that on average 397 euros are assigned per cow.

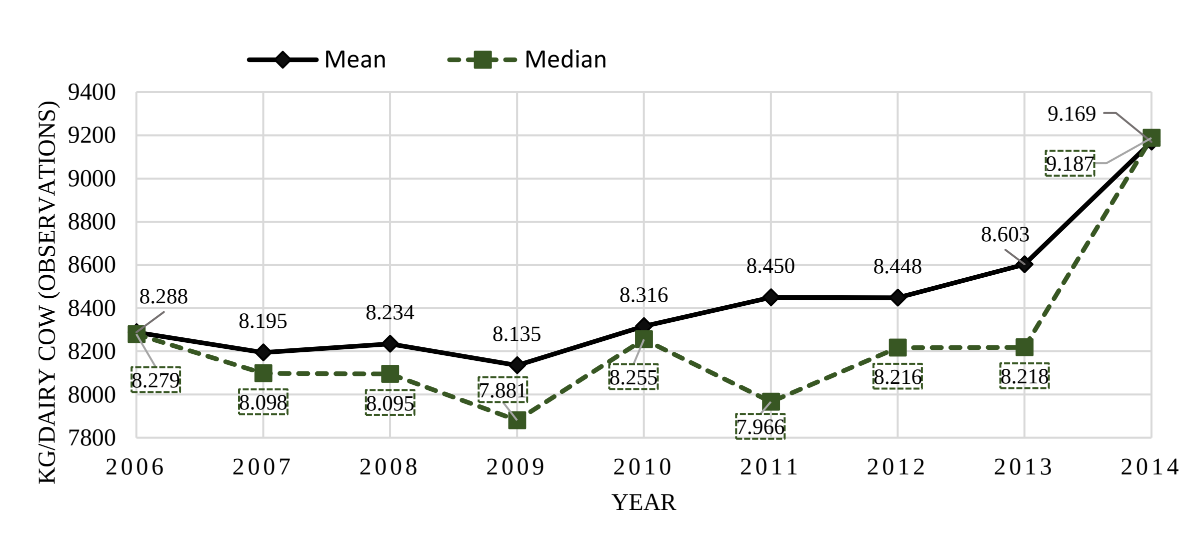

Figure 11 Cattle productivity over time

An introduction to the six animal indicators (Z1-Z6) was made in the animal welfare concept in the literature review.

The first animal indicator is the *calving interval*, which is on average 432 days (14.2 months). The shortest calving interval is 370 days (12.2 months) and the longest, 541 days (17.8 months).

The *interval to first calving* is on average 821 days (26.9 months). The majority of the cows in this sample (one standard deviation away from the mean) calved for the first time at the age of between 749 days (24.6 months) and 894 days (29.4 months). The earliest moment for a cow to calve for the first time was 663 days (21.8 months) after birth.

The *somatic cell count* (SCC) is an indicator of milk quality and is measured in somatic cells per millilitre milk (in thousands). On average, the SCC in this sample is 295,000 cells per millilitre. The lower and upper limits of one standard deviation from the mean are respectively 174,000 and 416,000. The values are generated using the geometric mean, which is the required method to comply with the European regulation on hygiene rules for food of animal origin (Commision, 2004). Furthermore, this regulation sets an upper limit of 400,000 somatic cell count per millilitre for raw cow milk of food business operators. Within this sample 207 (18%) of the observations lay above this threshold. In the paper of El-Tahawy & El-Far (2010) the cow condition is classified on the basis of the somatic cell count. With a somatic cell count of between 1,000-99,999, 100,000-199,999, 200,000-299,999, 300,000-399,999 and greater than 400,000 cows are respectively classified as normal healthy cow, normal cow with required observation for mastitis, cow susceptible to mastitis, cow affected with subclinical mastitis and cow suffering from mastitis. On the one hand, according to this classification, just 259 herds of the 1,160 observations are classified as normal cows or normal cows with required observation for mastitis. On the other hand, 476 herds are classified as cows affected with subclinical mastitis or cows suffering from mastitis. This statistic must be considered with caution, since it is constructed based on panel data. The herd of the same farm can be included several times in the statistic, because of subsequent years of observation. Since the farmer does not exchange the whole herd every year, the herd characteristics, like the somatic cell count, are similar for a farm throughout the years.

The *longevity* of the cow represents the herds’ lifespan and is on average 2,162 days (5.9 years).

The *genetic index* IGKL is an abbreviation for genetic index of kilograms of milk. It measures how productive the herd is in terms of kilograms of milk produced compared to an average cow. An average cow measures include information on its father and relatives of the bull. This measure is constructed using the summation of the deviation of the expected production from the cow to the average cow. The average value is 8,077 kilograms with a standard deviation of 221 kilograms. The difference between IGKL values for different herds is taken as indicator for the deviation from an average cow that can be explained by genetics and different ancestors.

Finally, the *insemination per calving* is, as discussed in the literature review, a direct measure of conception and partially an indicator of management expertise. The lower the number of insemination per calving, the more fertile is the herd, and the more experienced is the farmer. On average, the success rate for calving was 2.26 inseminations with a standard deviation of 0.44.

4.2. Model

The model of Battese & Coelli (1995) is used to analyse the data. The original model permits the estimations of both, the technological change and time-varying technical inefficiencies. Due to data problems, no time variable is included in the stochastic frontier, which would have accounted for possible technological change.

The stochastic frontier is constructed by the output *Milk* and the six inputs discussed before in a logarithmic form. The exogenous variables in the inefficiency equation are the different animal indicators. It was aimed at including all of the following six indicators: *Longevity, Interval to first calving, Somatic cell count, Calving interval, Number of inseminations per calving* and the *Genetic index*. However, including more than three exogenous variables or interaction terms at the same time. When including more than three animal welfare indicators the model did not converge for the estimation. Therefore, for each of the 20 possible combinations of three animal indicators a model is constructed (see Appendix 3). The stochastic frontier production function to be estimated is:

$$\begin{aligned} ln(Milk_{it}) = {} & \beta_0 + \beta_1 * ln(Labour_{it}) + \beta_2 * ln(Cows_{it}) + \beta_3 * ln(Concentrates_{it}) + \beta_4 \\ & * ln(Forage\ production_{it}) + \beta_5 * ln(Forage\ purchase_{it}) + \beta_6 \\ & * ln(Animal\ expenses_{it}) + V_{it} - U_{it} \end{aligned}$$

Where β denotes the unknown parameters to be estimated. The V_{it} is assumed to be the independent and identically distributed $N(0, \sigma_V^2)$ random errors. The technical inefficiency is a function of a set of the explanatory variables Z_{it} and the corresponding coefficients δ:

$$\mu_{it} = \delta_0 + \delta_1 Z_{it} + \delta_2 Z_{it} + \delta_3 Z_{it} + W_{it}$$

Here, the δ denotes the unknown coefficients of the animal welfare indicators and are to be estimated. The W_{it} is defined as a random variable which is defined by the truncation of a normal distribution with zero mean and variance σ_2. In general, the parameters of the stochastic frontier and the inefficiency equation are estimated simultaneously.

Based on the specifications above, 20 models are constructed of which five could be calculated using the STATA command *sfpanel*. Those five models and additional information about the model's goodness of fit are presented in table 3. The most suitable model is chosen based on the log likelihood statistics, the *Bayesian Information Criterion* (BIC) and *Akaike's Information Criterion* (AIC), as well as the theoretical framework and economic reasoning.

In general, the coefficient estimates for the production frontier variables of all the five models are statistically significant at the level of 1%. Furthermore, they are similar in their direction and magnitude. As an example, the production frontier variable *labour* varies by just 0.0036 (ranging from 0.0358 to

0.0394). The animal indicators *calving interval*, *interval to first calving* and *the somatic cell count* are positive and significant in each model, but vary in magnitude. The animal indicators *longevity* and the *genetic indicator* are in none of the models significant. *Insemination per calving* appear to be negative and significant in model 9 and 10. However, it shows no significant effect in model 11.

All of the models include 1,060 observations and have a degree of freedom of six. The log likelihood value indicates how good the model fits the data. For the five different models, the log likelihood ranches from 612 to 684. Those high values indicate that each of the models are suitable in explaining the data.

The BIC and AIC are used to make comparisons between models. The former is based on work by Raftery (1996) and used for this thesis as a decision making tool. Similar to the adjusted *R-Square*, the BIC statistic penalizes the inclusion of more variables. The more negative the value of the BIC, the better is the fit of the model. According to Raftery (1996) the difference between the models` BIC can be used to decide between models. As can be seen in table 2, if the difference in the BIC between two models is greater than 10, there is strong evidence to choose for the model with the smaller BIC. Model 8, 2 and 9 have the smallest BIC values of -1,320, -1,330 and -1,342, respectively. If we would choose between these models based on the difference table, we would select model 9, since it has an absolute difference of 12 and 22 to model 2 and 8, respectively.

Table 2 Difference criteria (Raftery, 1996)

Absolute Difference	Evidence
0-2	Weak
2-6	Positive
6-10	Strong
>10	Very Strong

However, under consideration of the theory, model 8 is selected. The animal welfare framework in the literature discussion shows that *insemination per calving* is theoretically a subpart of the *calving interval*. The same holds for the *interval to first calving*. Including just one of those two animal indicators in combination with the *calving interval*, would give results on two different levels and conclusions may be misleading, in a way that cause and effect relationships may not be visible. Evidence can be found in comparing model 2 and model 8. The magnitude of the effect of the *calving interval* on inefficiency of model 8 is 0.00133. In model 2 the overall measure *calving interval* is included as well as the *interval to first calving*. The effect of the *calving interval* (*interval to first calving*) on inefficiency is 0.00097 (0.000429). By adding those two, we discover that combined they account for a similar magnitude (0.001399) as the *calving interval* solely in model 8 (0.00133). The same reasoning, however, does not apply to the animal indicator insemination per calving in model 9. Consequently, it is argued that the *calving interval* is a suitable indicator and should be included in the model as a representative for the category: reproductive performance.

The *somatic cell count* is included in three of the five models presented in table 3. This indicator fits the animal welfare framework under the category: diseases/injuries.

Finally, we need to control for genetic variance between the farms as appeared from feedback and discussions with experts. By including the *genetic index*, it can be discovered whether there is an effect of genetics on technical inefficiency within this sample.

To sum up, model 8 is chosen for further analysis, because of a suitable BIC and high explanatory power of the included animal welfare indicators.

Table 3 Model choice

VARIABLES	Model 2		Model 8		Model 9		Model 10		Model 19	
	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu
Labour	0.0381***		0.0368***		0.0377***		0.0358***		0.0394***	
Number of cows	0.663***		0.659***		0.657***		0.657***		0.672***	
Concentrates	0.177***		0.179***		0.182***		0.177***		0.162***	
Forage production	0.0981***		0.0928***		0.0962***		0.102***		0.0908***	
Forage purchase	0.0210***		0.0210***		0.0209***		0.0238***		0.0253***	
Animal Expenses	0.113***		0.120***		0.116***		0.116***		0.117***	
Calving interval (days)		0.000970**		0.00133**		0.00256***		0.00562*		
Interval to first calving (days)		0.000429***								
Longevity (days)										0.000163
Somatic cell count		0.000569***		0.000663***		0.000773***				
IGKL (Genetic indicator)				-6.70e-05				0.000161		0.000134
Insemination per Calving						-0.151***		-0.312*		-0.0480
Constant	5.651***	-0.938**	5.644***	-0.264	5.597***	-1.090***	5.580***	-0.808	5.781***	0.657
Constant Usigma	-4.185***		-4.055***		-4.023***		-3.149***		-3.491***	
Constant Vsigma	-4.378***		-4.355***		-4.308***		-4.307***		-4.338***	
Observations	1,160		1,160		1,160		1,160		1,084	
Number of cod	197		197		197		197		188	
Log likelihood	677.9		672.9		683.8		653.7		611.8	
DF	6		6		6		6		6	
AIC	-1,330		-1,320		-1,342		-1,281		-1,198	
BIC	-1,264		-1,254		-1,276		-1,216		-1,133	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

5. Results and discussion

This chapter provides the reader with the results and discusses the production frontier, technical efficiency and the impact of animal welfare indicators on technical efficiency. It aims at answering research questions four and five. The chapter ends with research limitations and suggestions for further research.

5.1. Production frontier

All parameter estimates of the production frontier are positive and significantly different from zero at a 1% level. The production frontier estimates are interpreted as elasticity and can be found in table 4. As expected, an increase in inputs results in higher milk production per year. As an example, if the animal expanses increase by 1% the output of milk would increase by 12%.

Returns to scale refers to how much the output changes given a proportional change in all inputs. If the farm`s inputs are doubled and the output doubles as well, we speak of constant returns to scale. If by doubling the inputs, the output increases by less than the double (or more than the double) we speak of decreasing returns to scale (or respectively increasing returns to scale). This measure supports decision making with respect to operational size. The STATA command *test*[7] shows that the Chi-square test is highly significant, so we reject the null hypothesis and conclude that the summation of the coefficient estimates is unequal to one. Hence, we are confident that the farms in the sample are not operating on constant returns to scale.

Table 4 Parameter estimates of the stochastic frontier analysis

Variables	Parameter	Coefficient	Std. Dev.	95% Conf. Interval	
Production Frontier					
Labour	β1	0.0368***	0.0091	0.01896	0.05463
Number of Cows	β2	0.6590***	0.0218	0.61627	0.70174
Concentrates	β3	0.1787***	0.0146	0.15009	0.20727
Forage production	β4	0.0928***	0.0096	0.07406	0.11156
Forage purchase	β5	0.0210***	0.0033	0.01458	0.02748
Animal expenses	β6	0.1196***	0.0126	0.09497	0.14420
Inefficiency Equation					
Calving interval (days)	δ1	0.00133**	0.000589	0.00018	0.00249
Somatic cell count (SCC)	δ2	0.000663***	0.000229	0.00021	0.00111
Genetic indicator (IGKL)	δ3	-6.70E-05	5.40E-05	-0.00017	0.00004
Constant frontier		5.644***	0.1477	5.35462	5.93353
Constant Usigma		-4.055***	0.4911	-5.01729	-3.09217
Constant Vsigma		-4.355***	0.0985	-4.54836	-4.16225
Log Likelihood		672.9			

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

To test whether they operate on increasing or decreasing returns to scale, we use the STATA command *lincom*[8]. The sum of the coefficients is 1,108 with a standard error of 0.0094. At a 5% level and with a z-value of 117.63 this value is significantly greater than one. The 95% confidence interval is between 1.089 and 1.126. Hence, the production function exhibits increasing returns to scale. If we double the number of inputs, we would obtain more than twice as much outputs. Consequently, the Spanish dairy farmers in this sample could benefit from increasing the size of their operation.

[7] test _b[lnx1lab]+ _b[lnx2cow]+ _b[lnx3con]+_b[lnx4fprod] + _b[lnx5fpur] + _b[lnx6Aex]=1
[8] lincom [Frontier]lnx1lab + [Frontier]lnx2cow + [Frontier]lnx3con + [Frontier]lnx4fprod + [Frontier]lnx5fpur + [Frontier]lnx6Aex

5.2. Technical efficiency

Table 5 and figure 13 show the derived estimates of the two technical efficiency scores presented in the methodology section. As it was expected, the efficiency estimates JLMS and BC are very similar which can be attributed to the similarity of the calculations. The JLMS measure is used for further analysis.

Table 5 Technical efficiency scores

Variable	Mean	Std. Dev.	Minimum	Maximum	Variance	Skewness	Kurtosis
JLMS	0.906	0.051	0.653	0.984	0.00279	-1.570	5.734
BC	0.908	0.051	0.655	0.984	0.00273	-1.597	5.842

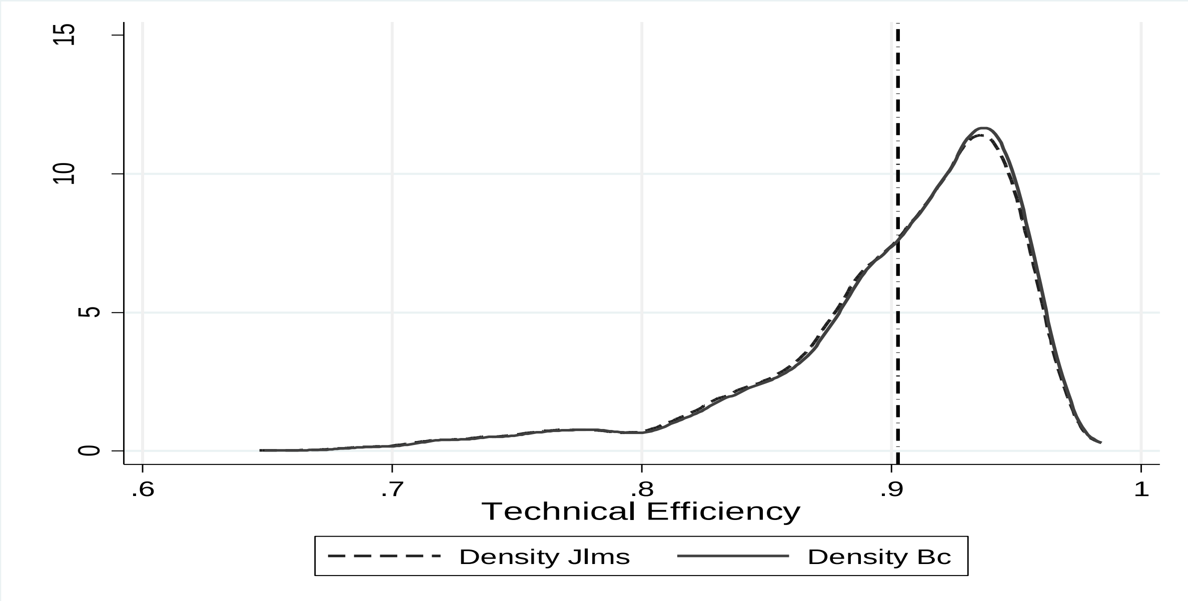

Figure 12 Density plot of technical efficiency scores

The average estimated efficiency score is 0.906, with the minimum value of 0.653 and the maximum value of 0.984. In general, the values range from zero to one and by multiplying the values by 100, the percentage of technical efficiency is calculated. Hence, on average, the technical efficiency is 90,6%. The kernel density distribution is negatively skewed (skewness of -1,570) and has a long left tail. Most of the technical efficiency scores (730 observations) lay above the mean value. Consequently, 430 of the observation lay below the mean value. It can be said that, the small amount of observations with relatively low technical efficiency scores shifts the mean value to the left.

This conditional mean of μ_i allows the researcher to make inference on the time trend of technical efficiency. Figure 14 displays the average technical efficiency with respect to nine consecutive time periods. The technical efficiency varied over the period of 2006 to 2014. The lowest technical efficiency occurs in year 2009 with 89,2%, whereas the highest is detected in year 2014 with 92,4%. As can be seen in table 6 the standard deviations of the sample means are small (ranging from 0.0034 to 0.0050) for all the nine years and the 95% confidence interval shows a small range between the lower and the upper bound. Hence, the mean value of technical efficiency for each year gives an accurate measure for the time trend.

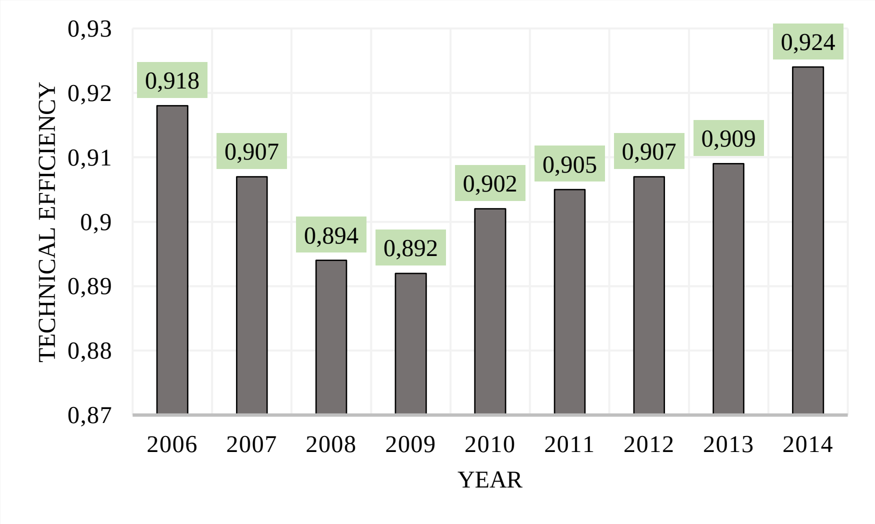

Figure 13 Technical efficiency over time

Table 6 Summery statistics technical efficiency over time

			95% Conf. Interval	
Year	Mean	Std. Dev.	Lower	Upper
2006	0.918	0.0034	0.9146	0.9214
2007	0.907	0.0042	0.9028	0.9112
2008	0.894	0.0044	0.8896	0.8984
2009	0.892	0.0048	0.8873	0.8968
2010	0.902	0.0043	0.8978	0.9063
2011	0.905	0.0047	0.9003	0.9097
2012	0.907	0.0050	0.9020	0.9120
2013	0.909	0.0049	0.9041	0.9139
2014	0.924	0.0046	0.9194	0.9286

Nevertheless, the magnitude of the total variation of technical efficiency over time within this dataset is just 3.2%. Hence, it is assumed that there were no external events or technological change within the sector, which influenced the dairy farm`s technical efficiency. With respect to the model of Battese & Coelli (1995), neglecting the time component in both, the production frontier and the inefficiency equation, can be advocated, since the change of technical efficiency for the period analysed is small.

5.3. Animal welfare indicator

Table 4 shows that the effect of the animal indicators *calving interval* and *somatic cell* count on technical inefficiency are positive and statistically significant at the 1% or 5% level, respectively. The general interpretation is that an increase in the *calving interval* and *somatic cell* count will increase technical inefficiency and hence be unfavourable for the farm. The genetic indicator is found to have no statistical significant impact on technical inefficiency within this sample.

Table 7 shows the inefficiency score and marginal effects of the animal indicators. On average, Spanish dairy farms in this sample could produce about 10% more output with the same amount of inputs. The marginal effect is calculated using the STATA command *predict*[9].

Table 7 Inefficiency and marginal effects

	Label	Mean	Std. Dev.	Skewness	Kurtosis
Inefficiency	-	0.100292	0.059799	1.903302	7.257309
	Label	Mean	Std. Dev.	Minimum	Maximum
Calving Interval	Z1_M	0.000445	0.000204	0.0001669	0.0012899
SCC	Z2_M	0.000222	0.000102	0.0000832	0.0006426
IGKL	Z3_M	-0.000022	0.000010	-0.000065	-0.000008

5.3.1. Calving interval

The marginal effect of the *calving interval* on technical inefficiency is 0.000445, with a standard deviation of 0.000102. The minimum value is 0.0001669 and the maximum value is 0.0012899. If the calving interval increases by one day, the technical inefficiency will increase by 0.000445 percentage points. The average calving interval of cows in this sample is 432 days (14.2 months).

The literature has reported mixed evidence on the relationship between calving interval and technical efficiency. An opposite effect was found by Lawson et al. (2004a) and Allendorf & Wettemann (2015). The former sampled Danish dairy herds that had an average calving interval of 12.91 months with a standard deviation of 0.26 months. The latter sampled German dairy herds that had an average calving interval of 13.41 months with a standard deviation of 0.66 months. Both studies concluded that a longer calving interval has a negative effect on technical inefficiency and hence improve technical efficiency. Similar to the results of this study, a second study of Lawson et al. (2004b) found that increasing the length of the calving interval results in increased inefficiency.

At the same time, results revealed that the magnitude of the marginal change is relatively small and so is the effect of a one-day increase of the calving interval. Extending the calving interval to 15 months (or 16 months) would result in an increase of inefficiency by 0.0107 percentage points (or respectively 0.0255 percentage points). However, as it is shown in the work of Allendorf & Wettemann (2015) there is an inflection point at which the increase of the calving interval will not any longer decrease, but increase technical inefficiency. Hence, the inclusion of a quadratic term of the calving interval could give more detailed insights into this aspect.

In comparison to studies of Louca & Legates (1968), Österman & Bertilsson (2003) and Lehmann et al. (2016) which used partial measures and discussed the impact of the length of the calving interval on productivity, this study stresses that a longer calving interval negatively affects the whole farm. It is important to know that the optimal calving interval which results in highest yields is between 12 and 13 months (Louca & Legates, 1968), however other factors than productivity , especially inputs, will be affected by this decision. Within this data set, decreasing the calving interval from 14.2 months to 12 or

[9] predict ineff_u, u // estimate of E(u)
gen eff_u=-ineff_u
predict, margin // predict the marginal effects, Z_M, of exogenous variables Z on E(u)

13 months may increase the yield, but definitely increases technical efficiency of the farm by 0.0298 or 0.0165 percentage points.

Finally, there is a trend of increasing the calving interval to enhance milk production (Oltenacu & Algers, 2005). This increase is correlated with high stress for the animal and reproductive problems (Oltenacu & Broom, 2010). Consequently, reducing the calving interval will not only increase technical efficiency but may reduce the stress for the animal and the incidence of reproductive performance resulting in better animal welfare.

5.3.2. Somatic cell count

The marginal effect of *the somatic cell count* on technical inefficiency is 0.000222, with a standard deviation of 0.000102. The minimum value is 0.0000832 and the maximum value is 0.0006426. If the somatic cell count increases by one unit (1,000 cells per millilitre), the technical inefficiency will increase by 0.000222 percentage points. The average somatic cell count of cows in this sample is 295,000 cells per millilitre.

Allendorf & Wettemann (2015) found that, up to a threshold of 160,000 cells per millilitre, an increase in somatic cell count increases inefficiency. However, beyond this threshold, unexpectedly, increasing the somatic cell count will decrease inefficiency. The combined effect shows that on average, technical efficiency increases by 0.51 to 0.54 percentage points as the cell count increases by 10,000 cells per millilitre. The average somatic cell count in their dataset was 185,900 cells per millilitre with a standard deviation of 39,900 cells per millilitre.

Producing milk on the upper level set by the European Union (400,000 cells per millilitre), would result in an inefficiency increase of 0.0233 percentage points. Consequently, it is desirable for the farmer to reduce the somatic cell count not only to avoid penalty fees by the European Union due to bad milk quality but also in order to increase the farm`s technical efficiency

As we have seen, El-Tahawy & El-Far (2010) classified the cow condition on the basis of the somatic cell count. According to their classification, most of the herds in this data set can be classified as *cows affected with subclinical mastitis* or *cow suffering from mastitis*. Hillerton & Berry (2005) stress that mastitis is a painful disease. Freedom from pain, injury and diseases is a growing requirement for animal care. Additionally, herds with high levels of mastitis produce milk with lower quality and entail higher costs due to for example higher veterinary costs and discarding of milk (Lightner et al., 1988; Pérez-Cabal et al., 2008). For several years, the milk production was oriented towards volume and the focus of mastitis treatment was rather the milk production than on eliminating the infection itself (Hillerton & Berry, 2005). Since, consumers and milk prices are more sensible to milk quality the focus changed into treatments aiming at bacterial elimination.

In summary, reducing the somatic cell count would not only diminish treatment costs and improve milk quality but also increases the farm`s efficiency and the cattle`s animal welfare. Hillerton & Berry (2005, p. 1254) see “further control of mastitis in the cow [as] a necessity” as well as a” major welfare requirement [for] the dairy farmer”. This study agrees to this assertion and adds the importance of a low somatic cell count for a good economic performance.

5.3.3. Genetic indicator

The genetic indicator, IGKL, is statistically not significant in this model and hence not further analysed. An explanation could be that the measure is not well defined to represent the difference in genetics or the sample shows low variance in genetics. A different measure for genetics used by Lawson et al. (2004a) is for instance to include information on the different breeds within the sample in the model. Lawson et al. (2004a) created dummy variables for three different breeds and included them in the inefficiency equation. This approach would provide a more detailed insight in the effect of genetics on technical inefficiency. However, the present data set did not provide the required information.

5.4. Limitations and further research

The objective of the study was to clarify if changing animal welfare of dairy cattle influences the technical efficiency of Spanish dairy farms. Two important indicators of animal welfare, namely the *calving interva*l and *SCC*, provided informative insights in the influence of animal welfare on technical efficiency. This study and the analysed literature highlight that whole farm analysis can add value to animal welfare discussions in an economic context.

With respect to this research, the dataset contained more information than were utilized within this study. The input variables used for the construction of the production frontier are well defined and contribute to solid estimates. However, the inclusion of animal welfare indicators in the inefficiency term could be improved. Animal indicators provided by the dataset such as the age of first calving, number of inseminations per calving and longevity are interesting to analyse in further studies. The results of the studies would generate insights in the effect of different animal indicators on technical efficiency and cover more aspects of the health and biological functioning component of the animal welfare framework.

With respect to the animal welfare framework, further research needs to address the following three interconnected areas. First, existing variables within the framework can be included in further research. Lameness for example can be analysed to discover the effect of another disease on technical efficiency. The requirement or obstacle to overcome is the generation of sound data on a lameness indicator, such as lameness scores. Second, the categories and measurements can be extended. As an example, the category diseases can be expanded by including a measurement on the dairy cattle disease *ketosis*. Finally, the focus of research can be broadened by including other components of the animal welfare framework. A subsequent study can be conducted in the field of natural living. A dataset on cow comfort, including information on pasture access or the flooring of the barn, for the same region in Spain is in process. A similar approach and model can be constructed to close the gap between animal welfare concerns and economic theories.

With respect to the econometric model, some aspects were already highlighted in the section above. In general, the model succeeded in explaining the effect of animal indicators on technical efficiency. However, the limitation of the model is that it allows just a restricted number and form of variables to be included in the inefficiency term. Including square terms or interaction terms would allow more detailed inferences. The effect of calving interval on technical inefficiency appears to be non-linear and therefore an inclusion of a square term of the calving interval would have been preferred. With respect to the interaction terms, the somatic cell count could be analysed more in detail by the inclusion of a cross product of the somatic cell count and the input variables in the inefficiency equation.

Besides the inclusion of different animal welfare indicators, it is recommended to include control variables such as a variable for technological change and a better indicator for genetic variance in further research. Within this research, the inclusion of a time component in the inefficiency would statistically prove whether there is a technological change for Spanish dairy farmers.

6. Conclusion

This study used a stochastic frontier model to discover the impact of animal welfare indicators on technical efficiency. The panel data model by Battese & Coelli (1995) was used to quantify the effects. The dataset consists of 197 different dairy farms in the region of Asturias, Spain and covered the period of 2006 to 2014. An animal welfare framework was created to conceptualize the term animal welfare and to discover how animal indicators are used in economic publications. A vast amount of indicators existed, which were classified according to the animal welfare framework. This study considered the inclusion of five animal welfare indicators, namely *longevity*, *interval to first calving*, *somatic cell count*, *calving interval* and *number of inseminations per calving*. Due to data problems and model specifications this study included only three animal indicators. Consequently, this study revealed the effect of the *somatic cell count,* the *calving interval* and *genetic differences* on technical inefficiency.

The average technical efficiency of Spanish dairy farms was 90,6% and evidence is provided that farmers can benefit from increasing their size of the operation. Based on the obtained results it was concluded that a reduction of both, the calving interval and the somatic cell count will reduce technical inefficiency of Spanish dairy farms. Reducing the calving interval form 14.2 months (432 days) to 12 months (or 13 months) will decrease technical inefficiency by 2,98% (or respectively 1,65%). However, increasing the calving interval can entail negative consequences for the animal welfare in terms of reproductive problems and animal diseases. The somatic cell count in the dataset was on average 295,000 cells per millilitre. Increasing the somatic cell count by 1,000 cells per millilitre increases technical inefficiency with 0.000222 percentage points. Kehrli & Shuster (1994) relate high somatic cell count to higher incidence of mastitis and reduced milk quality. Additionally, Hillerton & Berry (2005) stress that mastitis is a painful disease. Consequently, reducing the somatic cell count will not only increase technical efficiency but may improve animal welfare. The magnitude of the finding is small, but should incentive Spanish dairy farmers to reduce their herd`s somatic cell count in order to avoid penalty fees from the European Union and become more efficient.

In order to make more detailed inferences about animal welfare indicators, the used inefficiency equation could be modified. Further research is needed to bridge the gap between animal welfare and economic theories, whereby the use of whole farm measures is the proposed approach. This study can be replicated and applied to other animal welfare indicators in order to generate a better understanding of the interplay of animal welfare and economic implications.

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Appendices

Appendix 1: The abolishment of the milk quota

Due to a significant overproduction of milk, the common agricultural policy (CAP) introduced milk quotas in the Europe Union (EU) in 1984. Guaranteed milk prices were established and maximum amounts of milk production became fixed. Production beyond a certain threshold was punished by a levy. The EU subsidized the exports and together with the guaranteed prices, the farm revenues of dairy farmers were stabilized. After 2009, the European dairy sector was prepared for the abolishment of the milk quota in April 2015 by an annual increase of the milk quota by 1%. Paired with decoupled payments this ‘soft landing’ program allowed for a smooth re-integration of the EU in the world market. Production expanded and farmers profited from the growing market outside the EU. After the abolishment of the milk quota, farmers must pay more attention to the sector situation and market signals. The Milk Market Observatory program ensures transparency. Source: (Commission, 2017)

Appendix 2: Input use in the Spanish dairy sector

In comparison with the EU-15, Spanish dairy farms can be characterized as smaller farms which use less cows (on average 45 in Spain, 55 in the EU-15), less forage production area (24 ha, 51 ha) and less labour (1.72 annual work unit (AWU), 1.92 AWU). The labour at Spanish dairy farms is mainly family labour (87%), while the rest (13%) accounts for external labour. Since the forage production is relatively small (12 %), a vast amount of animal feed has to be purchased (93%). The feed prices increased significantly in Spain and feed costs account for about 60% of the operating costs. However, compared to the EU-15, the operating costs for Spanish dairy farms are low (276€/ton of milk produced), but also revenues are low (345€/ton of milk produced).(Commission, 2016)

Appendix 3: 20 Stochastic frontier models with different combinations of animal welfare indicators

Variables \ Models	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu
Labour	2.885		0.0381***		1.260		8.788		2.681		1.324		4.513	
Number of cows	1.358		0.663***		0.566		4.230		0.423		0.518		1.269	
Concentrates	4.504		0.177***		1.656		12.77		4.239		1.802		6.936	
Forage production	3.506		0.0981***		1.532		10.53		3.126		1.677		5.359	
Forage purchase	2.808		0.0210***		1.061		8.768		2.379		1.135		4.260	
Animal Expenses	3.296		0.113***		1.596		10.13		2.963		1.682		5.070	
Calving interval (days)		139.2		0.000970**		50.23		-441.1		117.5		53.71		212.1
Interval to first calving (days)		267.0		0.000429***		96.51		-843.4						
Longevity (days)		717.6								608.8		275.1		1,098
Somatic cell count				0.000569***						81.25				
IGKL (Genetic indicator)						958.0						1,024		
Insemination per Calving								-1.314						0.121
Constant	1.255	0.675	5.651***	-0.938**	0.117	0.881	3.215	-0.0225	-4.906	0.726	-0.765	0.873	-4.714	0.506
Constant Usigma	282.8		-4.185***		278.0		323.4		203.7		340.0		329.5	
Constant Vsigma	282.8		-4.378***		278.0		323.4		203.7		340.0		329.5	
Observations	1,084		1,160		1,160		1,160		1,084		1,084		1,084	
Number of cod	188		197		197		197		188		188		188	
Log likelihood	-154,644		677.9		-162,681		-189,067		-111,774		185,668		179,942	
DF	0		6		0		0		0		0		0	
AIC	309,288		-1330		325,362		378,134		223,549		371,336		359,883	
BIC	309,288		-1264		325,362		378,134		223,549		371,336		359,883	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Variables / Models	Model 8		Model 9		Model 10		Model 11		Model 12		Model 13	
	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu
Labour	0.0368***		0.0377***		0.0358***		3.028		0.845		2.550	
Number of cows	0.659***		0.657***		0.657***		0.776		0.242		0.974	
Concentrates	0.179***		0.182***		0.177***		4.423		1.094		4.223	
Forage production	0.0928***		0.0962***		0.102***		3.459		1.018		3.137	
Forage purchase	0.0210***		0.0209***		0.0238***		2.699		0.605		2.457	
Animal Expenses	0.120***		0.116***		0.116***		3.415		1.073		2.857	
Calving interval (days)		0.00133**		0.00256***		0.00562*						
Interval to first calving (days)								256.3		53.10		233.5
Longevity (days)								689.6		142.1		629.4
Somatic cell count		0.000663***		0.000773***				92.19				
IGKL (Genetic indicator)		-6.70e-05				0.000161				530.4		
Insemination per Calving				-0.151***		-0.312*						0.356
Constant	5.644***	-0.264	5.597***	-1.090***	5.580***	-0.808	-3.281	0.688	-0.927	0.934	-0.588	0.716
Constant Usigma	-4.055***		-4.023***		-3.149***		261.4		183.2		217.4	
Constant Vsigma	-4.355***		-4.308***		-4.307***		261.4		183.2		217.4	
Observations	1,160		1,160		1,160		1,084		1,084		1,084	
Number of cod	197		197		197		188		188		188	
Log likelihood	672.9		683.8		653.7		-143,024		-100,640		-119,228	
DF	6		6		6		0		0		0	
AIC	-1,320		-1,342		-1,281		286,048		201,280		238,456	
BIC	-1,254		-1,276		-1,216		286,048		201,280		238,456	

Variables / Models	Model 14		Model 15		Model 16		Model 17		Model 18		Model 19		Model 20	
	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu	Frontier	Mu
Labour	1.032		8.046		1.204		1.105		4.360		0.0394***		0.942	
Number of cows	1.111		2.938		0.431		1.159		1.564		0.672***		1.069	
Concentrates	1.585		11.93		1.754		1.678		6.050		0.162***		1.460	
Forage production	1.280		9.562		1.444		1.360		4.988		0.0908***		1.173	
Forage purchase	1.023		7.805		1.006		1.097		4.034		0.0253***		0.934	
Animal Expenses	1.271		9.116		1.459		1.349		5.038		0.117***		1.170	
Calving interval (days)														
Interval to first calving (days)		95.09		-752.7		92.02								
Longevity (days)								271.6		-1,042		0.000163		
Somatic cell count		33.69		-280.7				35.86		-139.5				30.60
IGKL (Genetic indicator)		944.0				913.9		1,011				0.000134		859.9
Insemination per Calving				-1.060		0.744				0.0605		-0.0480		0.759
Constant	5.657	0.883	-3.972	0.0886	-0.291	0.887	5.866	0.875	-1.509	0.533	5.781***	0.657	5.672	0.893
Constant Usigma	270.0		260.6		253.1		331.4		297.3		-3.491***		224.2	
Constant Vsigma	270.0		260.6		253.1		331.4		297.3		-4.338***		224.2	
Observations	1,160		1,160		1,160		1,084		1,084		1,084		1,160	
Number of cod	197		197		197		188		188		188		197	
Log likelihood	-158,051		-152,606		148,249		-180,974		-162,527		611.8		131,508	
DF	0		0		0		0		0		6		0	
AIC	316,102		305,212		296,499		361,948		325,053		-1,198		263,016	
BIC	316,102		305,212		296,499		361,948		325,053		-1,133		263,016	