The Regional and National Economic Effects of Sustainable Intensification

A Case of Dairy Farms in Wales and England

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Abstract

With the growing world's population, the demand for food is increasing. With an increase in demand, the supply of food should rise as well. However, increasing the production of food has consequences especially through the emissions of the greenhouse gases (GHG). The underlying theme of this study is the sustainable intensification (SI) in the dairy sector which aims to increase milk production while reducing the environmental impact.

This thesis aims to examine four research questions: Firstly, we want to assess if the intensification of dairy farms can reduce GHG emissions. Secondly, we want to determine if the intensity of the dairy farms improve their efficiency. Thirdly, we want to examine factors like location and other non-controllable variables that may influence the efficiency of the farms. Lastly, we want to see if there is a convergence in cost efficiency.

Data Envelopment Analysis is employed to measure efficiency. An undesirable output DEA is used to measure the technical efficiency of the dairy farms to examine increase in outputs such as milk and income while reducing output like GHG emissions. The results suggested that the dairy farms could potentially, on an average, increase their outputs by 4.2% to 8% while using the same level of inputs.

A two-stage approach is adopted to assess the factors that may influence the efficiency of dairy farms. In the first stage efficiency of dairy farms is evaluated and in the second stage Tobit Regression is employed to determine the factors that may influence efficiency. We found that age and land cost negatively while intensity, loans, tenure and the location of farms positively influenced efficiency. Finally, the convergence in cost efficiency is examined by borrowing from the growth literature. We saw evidence of convergence in cost efficiency implying that there is an improvement in cost efficiency in the dairy industry.

The results of this study suggest that the intensification of dairy farming through increasing stocking intensity can potentially reduce the GHG emissions per unit of milk and increase the efficiency of farms.

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Abbreviations

BCC	Banker, Charnes and Cooper
CCR	Cooper, Charnes and Rhodes
CH_4	Methane
CO_2	Carbon dioxide
COLS	Correct- Ordinary Least Square
CRS	Constant returns to scale
DEA	Data envelopment analysis
GHG	Greenhouse gases
GHGE	Greenhouse gas emissions
GVA	Gross value added
GWP	Global warming potential
ha	Hectares
hl	Hectolitres
IPCC	Intergovernmental panel on climate change
mt	Metric tonnes
N_2O	Nitrous oxide
OLS	Ordinary Least Square
SFA	Stochastic Frontier Analysis
SI	Sustainable intensification
UAA	Utilised agricultural area
VRS	Variable returns to scale

1. INTRODUCTION

The global demand for food is increasing as the population is growing. Tilman et al. (2011) projected that the global demand for food would increase by 100-110% from 2005 to 2050. It is projected that the world's population is going to increase by 2.4 billion from 2017 to 2050 (UN 2017). Apart from increasing population, the global food demand is also expected to rise due to expected future income growth[1]. As consumer's income increases their expenditure on food, particularly protein and meat, increases[2]. Dietary changes are significant for the future of food production systems as some food items require more resources such as land, water and energy to produce. It is projected that per capita meat consumption is going to rise from 37kg to 52kg per person per year from 2007 to 2050 (Bruinsma, J. 2009). Not only animal numbers would have to increase to cater to this rising demand but also crop production would have to increase to feed the animals.

With the rising demand for food, there is a need for an increase in its production. However, climate change poses a challenge to agriculture as extreme weather conditions can reduce the yield in some areas. Furthermore, many current farming practices harm the environment and contribute to global greenhouse gas (GHG) emissions. The UK GHG inventory reported that emissions from agriculture in 2017 amounted to 45.6 $MtCO_2e$ which is approximated 8% of the total UK GHG emissions (Brown, P. et al. 2017) . Without changes, current food production practices are likely to degrade the environment further and compromise the world's ability to produce food in the future (The Future of Food and Farming, F. 2011).

Agriculture contributes to climate change by emitting GHG, but is also affected by climate change (Campbell, B. M. et al. 2014). Changing climate will affect crop growth, livestock performance and agricultural yields. Extreme weather conditions are likely to become more severe and more frequent which would affect food production and food prices. The human population depends on livestock and crops as sources of food. A decline in crop yields would affect the human population twice. Firstly, the decline in crops would affect the human population through reduced food availability. Secondly, it would affect the livestock population, another source of food, who also depend on crops for sustenance. The need to provide food for a growing population while reducing negative environmental impacts is a key

[1] Relationship between food demand and income is non-linear and is described by Engel's law. The expenditure on food increases less than the increase in income.
[2] Bennett's Law

global challenge. An increase in food production needs to be achieved in such a way that it places less pressure on the environment and does not hinder the capacity of continued food production in the future (Garnett, T. et al. 2013).

An increase in food production is generally linked to intensification of the agricultural system. Intensification can occur either through increasing the production with the same land input or by increasing the farmed land to increase production. Increasing food production is a difficult task. First there is limited land available for agriculture and secondly, increasing land for agriculture requires the land to be cleared through deforestation which would significantly increase GHG emissions and lead to loss of biodiversity. Globally, the crop yields have increased by 115% between 1967 to 2007 however the agricultural area has decreased by 8% during the same time period (The Future of Food and Farming, F. 2011). In theory, increasing land for suitable food production can be achieved by allocating more land for such practices however there are also growing pressures to use to land in another capacity. For example, land is needed for urbanization, some land is lost due to rising sea levels or cannot be used due to desertification.

Thus, the current trend in intensification emphasises on increasing input utilisation without increasing physical land use. Intensifying the production though utilising the same land requires increasing fertiliser input and animal population on the farm which can lead to an increase in GHG emissions. Current food production systems need to change so that food production is increased without further deterioration of the environment.

Sustainable Intensification (SI) aims to increase the production of food while reducing the environmental impacts associated with farming. So, SI aims to improve the efficiency of production systems by increasing the output produced while lowering GHG emission per unit of output. Although no concrete definition exists for SI, there are certain factors that need to be met for a system to be sustainably intensive. Firstly, the system should increase farm output. Secondly, the production system should increase the output without requiring additional land. Thirdly, the production system should increase environmental sustainability.

So broadly, SI aims to utilise the existing available land to increase food production while simultaneously reducing the negative environmental impact associated with farming activities. SI of dairy farms in Wales and England is the underlying theme of this research. We strive to assess the environmental effects of dairy farming through the estimation of GHGs emitted from dairy production systems. Dairy farms are examined specifically in this study as they are one of the largest sources of agricultural GHG emissions. The current production of dairy output is evaluated with focus given on increasing farms' efficiency which may pave the way to increase food production while minimising environmental impact. In this study, SI is viewed as increasing efficiency of the farms while reducing GHG emissions. Since this study focuses on dairy farms, the gases methane (CH_4) and nitrous oxide (N_2O) are taken as greenhouse gases.

1.1. Research Questions

To examine sustainable intensification of dairy farms in Wales and England research questions have been developed to address a farm's efficiency, economically as well as environmentally. This study aims to answer four main questions that are outlined below.

Research Question 1: Does the intensification of dairy farms reduce GHG emissions

The first research question is the most important one. After reviewing the literature, we see a variety of mixed results. Some state that intensification can improve environmental sustainability while others argue that intensification leads to an increase in fertiliser use that may increase GHGs. We try to answer this question by using farm data provided by the Farm Business Survey (FBS) from 2006-2015 to determine the characteristics of intensive farms and to calculate the GHG emissions using the Intergovernmental Panel on Climate Change (IPCC) guidelines. The GHG emissions are taken as an indicator of environmental sustainability.

Research Question 2: Does intensification improve a farm's efficiency?

This research question assesses if the intensification of the dairy farms can improve their efficiency. The efficiency of dairy farms is measured using Data Envelopment Analysis (DEA). DEA is a non-parametric method that creates a linear frontier over the data. We estimate efficiency as farms using the correct proportion of inputs to generate maximum possible outputs.

Research Question 3: What factors determine a farm's efficiency? Does the location of the farms affect their efficiency? Are there non-controllable factors that may influence efficiency?

This research question ties to the social aspect of sustainable intensification. This research question aims to understand off-farm factors that may influences a farms efficiency apart from the main inputs and outputs used to create a frontier.

Research Question 4: Did the Welsh and English dairy farms exhibit convergence regarding economic efficiency from 2006-2014

The objective of this question is to examine if there is a presence of convergence in economic efficiency over the years. The convergence in economic or cost efficiency will help to determine if the farms with lower cost efficiency are catching up to the farms having higher economic efficiency.

1.2. The Structure of this Research

In chapter 2, we review the concept of sustainable intensification. The term sustainable and intensification is reviewed separately by investigating literature surrounding it. The need for agriculture to be intensive, sustainable to feed the growing world's population is evaluated by examining the GHG that are emitted during dairy farming.

Chapter 3 provides a conceptual look into dairy farming in the UK. We briefly examine the workings of dairy farms. The chapter also provides an overview of the trends in dairy farming.

Chapter 4 provides a comprehensive overview of the theory of efficiency. The different methodologies of estimating efficiency are reviewed. The merits of using DEA are put forward as the efficiency of dairy farms is examined using this technique in this thesis. The chapter provides an outline of the measurement of efficiency using DEA.

Chapter 5 outlines the data used for measurement of efficiency in this thesis. The chapter focuses on the main inputs and outputs of dairy farming which include land, the herd size, cost of feed, labour input and milk production. The emissions of GHGs, like methane and nitrous oxide are also calculated in this chapter using the guidelines by IPCC. The differences in an average Welsh and English farm over the 10-year sample period is also evaluated.

In chapter 6, we assess if the intensification of the dairy farm can increase a farms efficiency. The farms are grouped into clusters based on characteristics such as milk production per hectare and per cow a, stocking intensity and by GHG emissions per hectolitre of milk produced. Based on these characteristics, the farms are separated into two clusters; intensive and less intensive farms. Using the undesirable DEA model presented by Seiford and Zhu (2002), the technical efficiency of dairy farms in the UK is estimated.

Chapter 7 presents a two-stage approach of understanding efficiency. In the first stage, the efficiency of dairy farms using a variable returns to scale (VRS), output-oriented DEA is evaluated. In the second stage, Tobit regression is used to determine factors that may influence a farms efficiency like age and education of the farmer, ownership of the land, the intensity of the farms and other factors. Furthermore, regional variations in efficiency are also discussed in this chapter.

Chapter 8 measure the cost or economic efficiency of dairy farms using DEA. It also evaluates the presence of β and σ-convergence of cost efficiency scores of Welsh and English dairy farms. Structural variables are added to determine if the speed of convergence changes.

Finally, chapter 9 concludes the thesis, summarises the key findings and provides with a few policy implications. It also discusses the strengths and weakness of this research and presents future research possibilities.

2. THE CONCEPT OF SUSTAINABLE INTENSIFICATION

2.1. Introduction

Achieving global food security has become a challenge. The current world population of 7.3 billion in 2017 is expected to rise to 9.7 billion by 2050 (UN 2017). With the increasing population, the demand for food has increased and will continue to increase. The demand for cereal crops, for human and animal consumption, is projected to rise to 3 billion tonnes by 2050 from 2.1 billion tonnes in 2009 (FAO 2009).

To feed the growing world population, there is a dire need of increasing food production. An increase in food production can be achieved by either intensifying the production process or by expanding the land available for agriculture. However, an increase in the production of food by expanding land is difficult due to the limited availability of agricultural land (Scherer, L. A. et al. 2018). Therefore in recent years, an increase in food production has been achieved through intensification rather than through expansion (Foley, J. A. et al. 2011).

Agricultural intensification, however, has been labelled as one of the major contributors to climate change. Agriculture has contributed significantly to the emissions of greenhouse gases (GHG), soil and water degradation, loss of biodiversity and pollution due to the usage of fertilisers and pesticides (O'Brien, D. et al. 2014; DeLonge, M. S. et al. 2016). Agriculture is responsible for 30-35% of the global GHG emissions (Foley, J. A. et al. 2011).

With the rising demand for food, it has become increasingly important to change production systems which can improve the yields while reducing environmental impact. Many researchers have therefore emphasised the importance of sustainable intensification (Tilman, D. et al. 2011; Garnett, T. and Godfray, C. 2012).

Despite the existence of literature about the definition of sustainability and sustainable intensification (SI), no concrete definition exists. This chapter reviews the literature and aims to contribute to the existing definition of sustainability and sustainable intensification in agriculture which would then be used in the next few chapters to assess the sustainable intensification of dairy farms in the UK.

The structure of this chapter is as follows. In section 2 the concept of sustainable intensification is explored. A variety of literature regarding, agricultural sustainability and agricultural intensification is also reviewed. In section 3 the need of SI is evaluated with focus given on the GHG emissions resulting from agriculture. In section 4, we review the literature on sustainable intensification. Lastly, section 5 concludes the chapter.

2.2. What is Sustainable Intensification?

The intensification of production systems is very important as there is a need for an increase in food production. These production systems need to be sustainable so that these processes can fulfil the current demand and protect and preserve the environment.

The term sustainable intensification has been used in the context of African agriculture (Pretty, J. N. 1997; Garnett, T. and Godfray, C. 2012; Franks, J. R. 2014). In this case, agricultural output is low and environmental degradation connected with relatively low output levels is high.

Sustainable intensification might be understood as increasing productivity while reducing the harm to the environment, i.e. without cultivating more land (Firbank, L. G. et al. 2013). It is an aspiration of what needs to be achieved. Sustainable Intensification is still a recent concept so it is hard to say what it might look like or how it would be different from the production systems currently in play.

The Montpellier Panel, T. M. (2013) explained Sustainable Intensification as:

> "Sustainable Intensification offers a practical pathway towards the goal of producing more food with less impact on the environment, intensifying food production while ensuring the natural resource base on which agriculture depends is sustained, and indeed improved, for future generations."

Although consensus has not been made on the accurate definition and description of sustainable intensification (Pretty, J. N. 1997; Petersen, B. and Snapp, S. 2015), all researchers agree that sustainable production systems should show certain attributes:

- A sustainable production system should avoid unnecessary use of inputs (Pretty, J. N. 1997)
- A sustainable production system should minimise the extra use or misuse of technology which harms human and animal health and the environment.

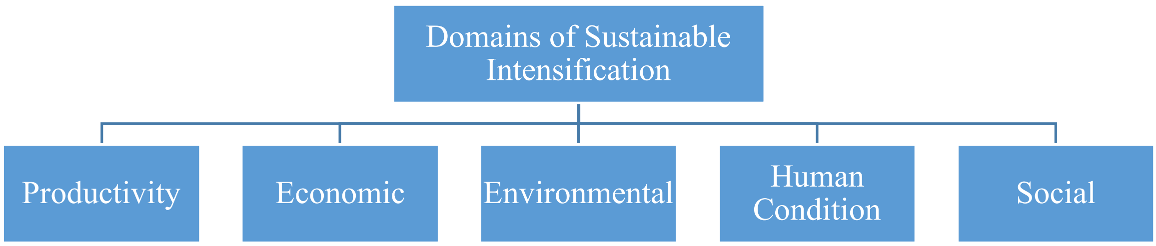
- A sustainable production should make productive use of human capital in the form of innovation, knowledge and adaptability (Pretty, J. N. 1997).

- The production should minimise externalities such as GHG, biodiversity and clean water.

The agricultural systems which possess these attributes can be classified under SI. These systems would then be diverse which not only focus on the increase in production of the food source but also would work towards contributing to social welfare. The framework developed for SI needs to be specifically tailored for the respective area or industry. SI cannot be achieved globally by applying the same framework to every area and every system.

According to the literature, the indicators of sustainable intensification are categorised into five key domains (Smith, A. et al. 2017). These five domains are presented in Figure 2.1.

Figure 2. 1: Domains of Sustainable Intensification



The productivity domain captures the productivity of crop and the livestock output. It includes indicators such as yield, fodder production, yield gap and yield variety. An increase in productivity is one of the goals of SI. The second domain is of economics which looks at the profitability, costs and the return to the factors of production. The productivity domain is specifically dealing with the increase in productivity from only the land as input whereas the economic domain includes the remaining inputs like labour and capital. The economic domain deals mostly with the profitability of the agricultural system where the farmers' decision to grow crop and allocation of resources strictly depends on the demand for the produced commodity in the market.

The third domain is for the environment in which focuses on plant diversity, nutrient balance, GHG emissions and soil and water quality. The environmental domain is one of the key pillars of SI where the focus is not only on the improvement in output but also on protecting the environment. The fourth domain examines the individual. It focuses on the human conditions and their accessibility to proper nutrition, health and education. The last domain is the social aspect which looks at gender equality, social cohesion and collective action.

The domains of sustainable intensification are primarily based on the composite indicators of sustainability[3]. The productivity, economic and environmental domain are mostly used as a part of composite indicators when measuring agricultural sustainability (Dantsis, T. et al. 2010; Gómez-Limón, J. A. and Sanchez-Fernandez, G. 2010; Barnes, A. P. and Thomson, S. G. 2014). The human condition domain can be characterised as a part or an extension of the social domain whereas the domain of productivity can be classified as an extension of the economic domain.

Before reviewing the literature on sustainable intensification, we first need to understand what the term sustainability and intensification mean, separately. In the next section of this chapter, we review the literature on sustainability and intensification.

2.2.1. <u>Sustainability</u>

The sustainability of agriculture has gained traction in recent years. The growing interest in sustainable agriculture, especially in the developing countries, has been due to the limitation of the conventional agricultural systems which negatively impact the environment (Gafsi, M. et al. 2006).

Ecologists, biologists, economists and sociologists have all provided insight into the concept of sustainability and created definitions suitable for their own fields (Faber, N. et al. 2005). The concept of sustainability gained traction as improvements in the economic performance of the farms led to degradation of the environment. According to Faber, N. et al. (2005)

> "Semantically, sustainability indicates a relationship between a (sustainable) artefact and its environment that exists indefinitely. In other words, sustainability refers to an equilibrium

[3] The composite indicators of sustainability are discussed in detail in next section

between an artefact and its supporting environment, where they interact with each other without mutual detrimental effects. Sustainability explicitly refers to this equilibrium."

Sustainability can be thought of as satisfying people's needs without compromising their choices or the choices of future generations (Struik, P. C. et al. 2014). (Caiado, R. G. G. et al. 2017).

Measuring agricultural sustainability

When talking about sustainability in agriculture, many definitions exist which try to satisfy some given set of conditions defined under sustainable development (Gómez-Limón, J. A. and Sanchez-Fernandez, G. 2010). The World Commission on Environment and Development (WCED) defined sustainable development as:

"Development, which meets the needs of the present without compromising the ability of future generations to meet their own needs". (WCED 1987)

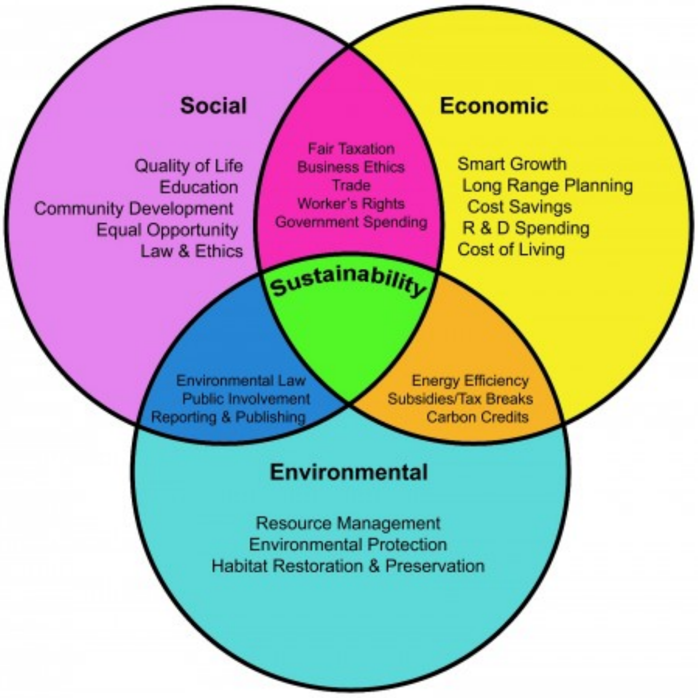
The United Nations identified a series of indicators of SD and urged the government and non-government organisations to "develop and identify indicators of sustainable development in order to improve the information basis for decision-making at all levels" (UNCED 1992).

The initial program on the indicators of sustainable development came forward with the list of 134 indicators which was later shortened and divided into 14 sections: poverty, governance, health, education, demographics. Natural hazards, atmosphere, land, ocean, seas and costs, biodiversity, economic development, global economic partnership and consumption and production patterns.

No consensus has been achieved on how to measure sustainability. Using the themes of sustainable development provided by WCED (1987), a farm is classified as sustainable when it can satisfy the economic, social and environmental conditions. A variety of studies have used these themes to create composite indicators/indexes of sustainability (Dantsis, T. et al. 2010; Gómez-Limón, J. A. and Sanchez-Fernandez, G. 2010; Barnes, A. P. and Thomson, S. G. 2014).

Figure 2.2 shows the three essential components of sustainability used to create composite indicators: environment, social and economic aspect.

Figure 2. 2: Composite Indicators of Sustainability (Koskinen, O. 2016)



The composite indicators (CI) for sustainability are constructed when analysing the environmental, social and economic change in farms as only one indicator would not provide enough information to the policymakers (Barnes, A. P. and Thomson, S. G. 2014). The composite indicators of sustainability allow researchers to combine indicators into one index based on the underlying concept of a production system. These indices help the policymakers to condense all information and makes it easier for them to compare and make decisions. These composite indexes, if well-constructed, would be able to monitor environmental conditions as well as observe the trend due to changes in the policy (Giannetti, B. F. et al. 2009; Sabiha, N.-E. et al. 2016).

The construction of CI of sustainability is a three-step process. The first step is a theoretical step where the environmental experts select the underlying variables (Esty, D. C. et al. 2005; Giannetti, B. F. et al. 2009). The selection of variables is based on the theoretical framework of the production system being evaluated. In the second step, the data are collected of the variable selected in the first step. Special attention needs to be given to the relationship between variables and the indicators chosen. Correlation analysis is performed to eliminate highly correlated indicators.

In the last step, the collected data are then normalised and aggregated into an overall index. This index is then used for decision making, policy making and performance comparison purposes (Zhou, P. et al. 2006; Giannetti, B. F. et al. 2009). The indexes constructed should be relevant, flexible and should be able to apply to a broader range of systems (Sabiha, N.-E. et al. 2016). A variety of CI has been proposed by the literature to measure sustainability.

The Environmental Sustainability Index (The Future of Food and Farming, F.) was published by the World Economic Forum in collaboration with Esty, D. C. et al. (2005). They produced 21 environmental performance indicators to help compare the issues of environmental variables in 146 countries. The indicators were then divided into five categories; environmental systems, reducing environmental stress, reducing human vulnerability, social and institutional capacity and global stewardship. The components of the environmental system include indicators which measure air and water quality, land and biodiversity. Reducing environmental stresses include indicators which measure the reduction in population and waste. It focuses on the effective management of natural resources and air pollution. The component on reducing human vulnerability includes basic human health, natural disaster management and environmental health. This component measures the externalities caused by environmental harm. The availability of technology, responsiveness of private sector and environmental government comes under social and institutional capacity. It measures the social aspect of sustainability such as the effectiveness of government, implementation of law and quality of education. The last component of ESI is global stewardship. It considers the country's effort to collaborate with international partners on reducing the environmental stresses. It also includes indicators for greenhouse gas emissions by measuring carbon emissions per capita and per million US dollar GDP.

A higher score of ESI showed that those countries would be able to maintain favourable environmental conditions in the future. The highest-ranking countries were Finland, Norway, Uruguay, Sweden and Iceland as they all had large quantities of natural resources and had a low population density. However, countries like North Korea, Iraq, Taiwan, Turkmenistan and Uzbekistan scored low due to the natural and man-made problems which made policy implementation very difficult. Richer countries performed better in human vulnerability and social and institutional capacity. The poorer counters scored higher in reducing the environmental stresses and environmental systems. They also performed a cluster analysis to determine the peer countries. It was done so that the countries could judge and compare their performance against the countries they believe were like them. The clusters were formed using the five components of ESI and key performance indicators such as GDP per capita, population and area. The results showed that clusters included many counties that were geographically close to one another. This result was unexpected as no geographical data was used for the analysis.

Agovino, M. et al. (2018) constructed CI called the index of sustainability agriculture for the EU- 28 from 2005 to 2014. The environmental indicators included energy consumption in agriculture, electricity generated by renewable sources and GHG emissions in agriculture. The economic indicators included real GDP per capita, the employment rate in education, unemployment rate and income from agriculture activities. Lastly, the social aspect of CI included variables like gender employment gap, people at risk for poverty and adult's participation in employment. They used the composite indicators to test the relationship between agricultural yields and climate changes. They found that there was a negative and bidirectional relationship between climate change and agricultural yields.

Sabiha, N.-E. et al. (2016) presented a study where they constructed a Composite Environmental Impact Index (CEII) for rice farming in the North-West part of Bangladesh. Their model used three types of indicators for the CEII. The first indicator was a mean based indicator which included variables for production. The second indicator was effect based which included variables for the farming system like soil and water quality. The third indicator was the perception based indicator which included the variables associated with the farmer's perception. The scores showed that the intensive rice cultivation was the cause of natural resource depletion and caused significant environmental degradation.

Dantsis, T. et al. (2010) compared the economic, social and environmental aspect of sustainability at a regional level in Greece. The environmental indicators included the use of fertiliser, pesticides and water on the farms. They also focused on the farm management practices. This included the management of manure, crop rotation and the effectiveness of machinery used on the farm. In the social aspect, they looked at the age of the farmer, their education level and the size of the household. Under the economic aspect, they evaluated the financial resources of the farms and the farm structure. They found that the areas with low farming intensity had higher levels of environmental sustainability. The intensification of the farms was reflected using fertiliser. The social sustainability was higher in the areas that had well-educated farmers and was lower in the area where the farmers were younger, and the size of households was larger. Lastly, they found that the larger farm in terms of area and diversified farms were less economically sustainable and performed worse, financially.

2.2.2. What is intensification?

Before the industrial revolution, agriculture was based on household units, where individuals grew crops or kept livestock for their personal consumption. A single unit generally did the production, processing, and consumption. With the improvement of farming technique over time, farming surplus emerged, and individual units were producing more than they could consume. This process was helped by technical advances, particularly with more potent fertilisers and pesticides yielding a higher agricultural output. Moreover, selective breeding improved the quality as well as the quantity of meat and crops produced. (Bos, J. F. F. P. et al. 2013)

Intensive agricultural practices have come to threaten traditional farming practices and landscape which has evolved for centuries. Advancement in technology has led to the extinction of traditional landscape (Antrop, M. 1997). Changing landscape has not only been attributed to technological advances. Other forces that derive the change in the landscape are accessibility, urbanisation, globalisation and calamity (Antrop, M. 2005). The areas that are less accessible have more natural landscape. However, with new transportation infrastructure, a change in landscape can be seen immediately. Population growth, urbanisation and changes to the pattern of food consumption drive agricultural intensification where farmers start to produce more food to satisfy the demand. It is done by increasing the inputs or/and by using those inputs more efficiently (Struik, P. C. et al. 2014).

Intensification is defined as the production of more output units given a level of inputs. Agricultural intensification can be explained as maintaining a certain level of agricultural output while decreasing the use of inputs (FAO 2004; Salou, T. et al. 2017). Struik, P. C. et al. (2014) defined intensification as "Increasing the level of input of any kind to increase physical or economic productivity". The physical inputs for agriculture include land, labour, machinery, capital and fertiliser and pesticide use.

A variety of studies have evaluated agricultural intensification. Some of these studies used an increase in fertiliser application (Dantsis, T. et al. 2010; Cardoso, A. S. et al. 2016; Levers, C. et al. 2016) or increase in concentrate use (Llanos, E. et al. 2018) as a sign of intensification. Some studies defined intensification as an increase in output per animal (Caviglia-Harris, J. L.

2018) or per land area (Meul, M. et al. 2007; Stott, K. J. and Gourley, C. J. P. 2016; Chobtang, J. et al. 2017b; Salou, T. et al. 2017; Woldegebriel, D. et al. 2017) . Other studies identified intensification as having the higher number of animal per hectare of land (Caviglia-Harris, J. L. 2018).

Some studies have found that intensification based on increasing in inputs has had a severe impact on the environment. Intensification when measure as an increase in fertiliser use is generally associated with increasing GHG emissions. Dantsis, T. et al. (2010) found that increasing fertiliser application increased farms' output but reduced fossil fuel energy efficiency. Stott, K. J. and Gourley, C. J. P. (2016) found that intensification based on an increase in milk production per hectare lead to an increase in Nitrogen losses to the environment.

Llanos, E. et al. (2018) found that an increase in concentrate use increases milk production per animal but reduced energy efficiency. Sustainable intensification should be based on efficient utilisation of pasture rather than increasing the use of concentrates. Similarly, Chobtang, J. et al. (2017a) also found that intensification, if coupled with increasing pasture utilisation efficiency can lead to environmental sustainability and increase animal's productivity.

However, Meul, M. et al. (2007) who assessed energy use efficiency of specialised dairy, arable and pig farms found that the intensive farms were the most energy efficient as they combined high production with low energy use. Van Apeldoorn, D. F. et al. (2013) used the increase of milk production as a sign of intensification of production in Dutch dairy farms. They showed that agricultural intensification heavily depends on the landscape characteristics of a farm.

Intensification can also be measured in terms of net income generated per unit of input. Llanos, E. et al. (2018) found that intensifying dairy farms by increasing the amount of concentrated feed lead, sometimes, to an increase in net income per hectare.

Economic drivers of intensification in agriculture

An increase in the global demand for animal based food has directly affected livestock production systems (Bernués Jal, A. and Herrero, M. 2008). New demands have led to an expansion of cultivated area, intensification of production systems and closer integration between crop production and livestock numbers. Intensification of production can be view as an endogenous and exogenous process due to changes in technology and population pressure, respectively. The next part of this chapter discusses these processes in detail.

Technology treadmill

The term 'technology treadmill' was introduced by William Cochrane. Cochrane, W. W. (1958) said that there was a cyclic process of creating a new technology which results in a reduction in costs, increase in the supply, a reduction in market prices and an increase in the size of the farm. Early adopters of technological innovations had more to gain as they could produce more and thus sell more at a lower cost. It resulted in an increase in farm's income which drove down market prices. Late adopters of new technology saw a decrease in their farm income as the market prices fell. Late adopters were subsequently forced to adopt new technology or face extinction. This resulted in a treadmill like effect where famers strove to adopt new technology so that they could stay ahead of declining market prices.

This technology treadmill effect resulted in intensification of farms. There was a shift to larger farms as smaller farms were unable to cope with competition. Farmers who were unable or unwilling to adopt new technology were forced to either exit agriculture and/or become passive landowners. The land resource was then acquired by innovative farmers resulting in an increase in farm size and reduction in total number of farms (Chatalova, L. et al. 2016). One example of this trend is the Dutch dairy industry where farms increased their productivity while simultaneously reducing the total number of dairy farms. (Struik, P. C. et al. 2014).

Population pressure

Another driver of agricultural intensification is the growth of population and the need to access the market. The links between population growth and agricultural intensification were considered by Boserup, E. (1965) and Ruthenberg, H. (1971). A common observed pattern was that in areas with low population density, farmers cultivated land for a few years until its fertility reduced. At this stage the farmer moved to another area while leaving the previous land to recover its lost nutrients (Nin-Pratt, A. 2015; Binswanger-Mkhize, H. P. and Savastano, S. 2017).

However, as population density increased, the demand for land grew as there were competing uses, and farmers had to intensify production (Binswanger-Mkhize, H. P. and Savastano, S. 2017). Intensification led to income maintenance as well as an increase in food supply. Farm intensification also led to an increase in labour requirement per unit of land which has been shown to be connected to higher yielding crops (Binswanger-Mkhize, H. P. and Savastano, S. 2017).

One criticism of the Boserupian model is that the model is based on a closed economy which is not ideal for the current economic situation. Due to it being closed in nature, the model doesn't take into consideration the exogenous factors and neither does it consider the ease of accessibility of foreign markets. Furthermore, even in the areas which have low population density, there is still a growing demand for the products as new markets can be easily accessible which drives up the demand for land and in turn leads to an intensive use of land (Nin-Pratt, A. and McBride, L. 2014). The intensity of land usage is calculated by looking at the use of purchased inputs and the level of output produced per hectare. The population density is measured as the number of people per hectare of farm land(Nin-Pratt, A. and McBride, L. 2014).

2.3. The need for Sustainable Intensification

The main drivers of the agriculture process are the use of land and according to the report by FAO, we have seen only 11% increase in agricultural land from 1961 to 2007 as most of the usable land is already being used for intensive agriculture (Tilman, D. et al. 2002). At the same time, world's population has grown 123%. Furthermore, the agricultural area in the industrialised country has decreased, and as the cities grow, less emphasis is placed on maintaining the agricultural land. In addition, labour force participation in agriculture is decreasing as the focus of countries is shifting from agriculture to manufacturing which is considered more profitable. This has placed a heavy burden on the agricultural system that need to drastically improve their productivity to cater to the growing masses.

There are certain constraints on the production of food which vary from region to region. To meet the demand for food, the farmers must intensively farm their land. The intensification of farming increases the production of food but, sometimes it negatively affects the environment (Erisman, J. W. et al. 2013; Stott, K. J. and Gourley, C. J. P. 2016; Llanos, E. et al. 2018).

Agriculture impacts the environment through the emissions of GHG. These GHGs contribute to climate change which in turn affects agriculture and contributes to the reduction in food production. Thus, climate change and agriculture are interrelated processes which affect one another. Climate change affects agriculture through changes in temperature, rainfall, diseases and changes in sea level and agriculture contributes to climate change through the emission of GHG and land use changes through deforestation.

Climate change results in an increase in CO_2 levels. A higher CO_2 level affects the yield and the quality of the crops. Changes to the temperature and rainfall highly impacts agriculture. An increase in temperature and changes in the patterns of precipitation affect growth of the crops. A rise in temperature and lack of precipitation leads to drought and causes the soil to become dry. This, in turn, prevents the farmers to produce optimal yield. In some places, it is possible that an increase in irrigation can manage this problem, but this cannot be said for regions that lack in capital and resources.

Even though less than 20% of the world's croppable area is irrigated, it produces about 50% of the world's food (Döll, P. and Siebert, S. 2002). Although the irrigation systems are quite beneficial to the crop production, they also cause a threat to the general environment. An increase in irrigation systems lead to a reduction in river flows which degrades the environment and causes the acceleration of desertification (Ma, J. W. et al. 2003).

Warmer temperature and wetter climates lead to an increase in pest, fungi and weed which thrive under these conditions and disease the crops. Changes in the pattern of temperature and precipitation also lead to degradation of the quality of the soil. The soil is fundamental for the crop production, and extensive land use can cause a loss of nutrients in the soil. A loss in the nutrients provided by the soil would lead to a decrease in the yield. To combat this problem, the farmers tend to rely heavily on the application of pesticides and fertilisers.

Although these fertilisers help the soil to regain its lost nutrients, the toxins in the fertilisers would seep into the groundwater causing harm to human and animal health (Tilman, D. et al. 2002). Without the use of synthetic fertilisers, food production would not have increased as much as it did. So even though the use of fertiliser can pose an adverse effect on the environment, it is not possible to remove them entirely from the production system. To combat this problem, there is a need of improving nitrogen use efficiency in farming systems (Tilman, D. et al. 2002).

With the increase in industrialisation, the waste material from production has also increased. It is costly to manage waste so many of them dump their waste into the water bodies close by or dump it directly onto the land. These pollutants from the factories seep into the soil and pollute it. Regulations have been made to stop these practices so that the environment can be protected, but it is tough to implement these rules especially in the developing countries (Solazzo, R. et al. 2016).

The agricultural processes produce GHG which also cause the climate to change. In 2013, agriculture contributed to a total of 10% of CO_2 emissions, 54% of CH_4 and 79% of N_2O emissions in the EU area (EEA 2015). The farmers usually overlook these environmental impacts and they often go unmeasured as they do not influence farmers choice about the production system (Tilman, D. et al. 2002).

2.3.1. GHG emissions

Agriculture is one the main contributors to global warming and climate change through the emissions of greenhouse gases (GHG) (Del Prado, A. et al. 2010; Kristensen, T. et al. 2011). Among all the agricultural sectors, livestock farming contributes the most to GHG emissions. The production of milk and beef contributes to 9% of the global GHG emissions (Styles, D. et al. 2017).

The Kyoto Protocol[4] brought forward six important GHGs namely: Carbon dioxide (CO_2) Methane (CH_4) Nitrous Oxide (N_20); Perfluorocarbons (PFCs); Sulphur hexafluoride (SF_6) and Hydrofluorocarbons (HFCs) (UN 1998). The main gases produced by livestock farming are methane (CH_4), carbon dioxide (CO_2) and nitrous oxide (N_2O).

Table 2.1 presents the main GHG emissions from livestock farming and the sources of these emissions.

Table 2. 1: GHG emissions sources from livestock farming

Methane (CH_4)	Carbon dioxide (CO_2)	Nitrous Oxide (N_2O)
Enteric fermentation	Fuel combustion	Manure Management
Manure Management	Land use change and degradation	Fertiliser

Methane is emitted during livestock farming through the process of enteric fermentation and manure management. The emissions of methane from enteric fermentation occurs in the digestive system of ruminant animals. Enteric fermentation produces methane as a by-product

[4] The Kyoto Protocol is an agreement reached in Kyoto Japan in 1997 amongst industrialized countries to cut their GHG emissions. It is a legally binding agreement between the countries that they will reduce their combined GHG emissions by 5.2% compared to the year 1990.

in the rumen of the animal while the feed is being digested and so the intake of feed is one of the major drivers of methane production (Negussie, E. et al. 2017). Methane is also produced through manure management during the storage and the treatment of manure. Manure is decomposed under anaerobic conditions during its storage and produces methane.

Carbon dioxide is emitted from livestock farming though the combustion of fuel. The running of a farm requires machinery, tractors, harvesters and milking machines which either use fuel or electricity for operations. The carbon dioxide is also emitted from land use changes though the conversion of land from forest to agricultural land. Lastly, nitrous oxide is emitted though manure management and application of fertiliser on the soil. The emissions of nitrous oxide occur directly and indirectly on the farms thought the process of nitrification and denitrification.

To compare the contribution of different GHGs, a relative measure of Global Warming Potential is used. The GWP is a relative measure of how much heat a GHG traps in the atmosphere (DEFRA 2018b). The GWP is calculate over a specific time interval like 20, 100 or 500 year however the GWP for 100 years is unusually taken as the reference. The GWP for each gas is given as its warming influence relative to carbon dioxide. The GHGs are then presented in carbon dioxide equivalents. The GWP for the three main GHG in livestock farming is presented in Table 2.2.

Table 2. 2: GWP for a given time horizon

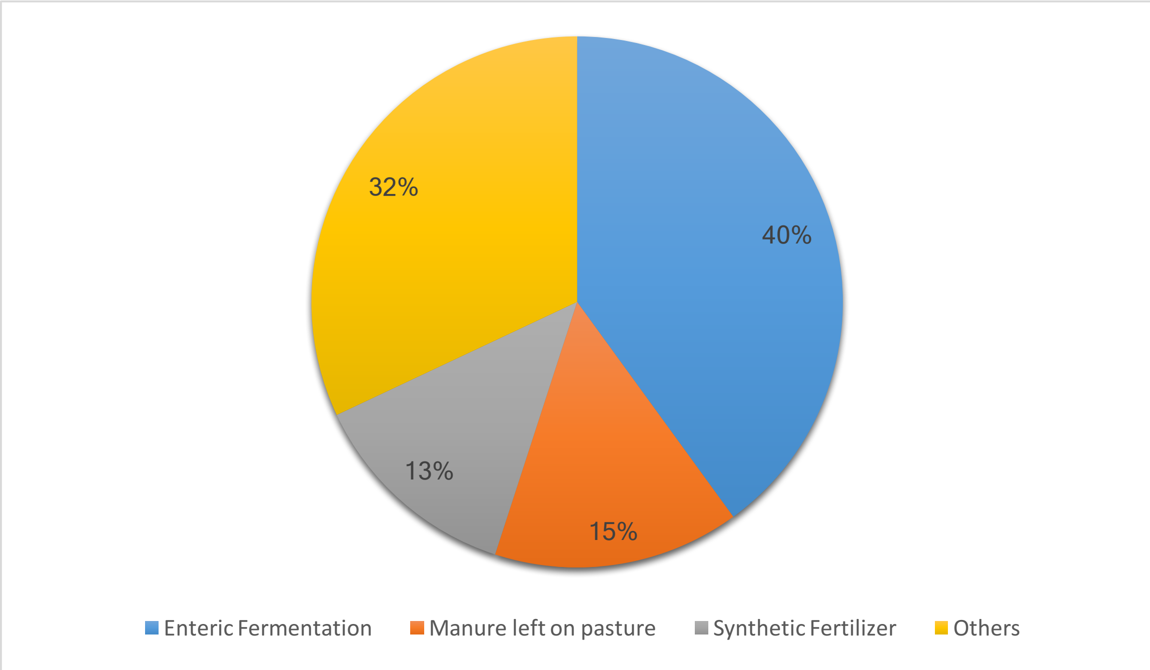
GHG	20 years	100 years	500 years
CO_2	1	1	1
CH_4	72	25	7.6
N_2O	289	298	153

Source: IPCC (2006)

Among the agricultural GHGs, Nitrous oxide is the most potent GHG with GWP ranging from 153-298 kg CO_2 equivalents for 20 to 500 years. Methane emission has a GWP of 7.6 to 72 kg CO_2 equivalents for 20 to 500 years.

Even though the N_2O is the most potent of the agricultural GHGs, the largest contributors of agricultural emission are the emission of methane from enteric fermentation. The emissions from enteric fermentation contributed 40% to the total emissions from 2001-2011 as shown in Figure 2.3. The emissions from enteric fermentation are followed by the emissions from manure left on the pasture (15%) and then emissions due to the application of synthetic fertilisers.

Figure 2. 3: Agricultural emissions (2001-2010)



Source : Tubiello, F. N. et al. (2014)

Using Intergovernmental Panel on Climate Change (IPCC 2006) guidelines, the emissions from methane and nitrous oxide are estimated in Chapter 5.6. The IPCC is an intergovernmental body under the United Nations which produce reports on the methodology of estimation of GHGs.

In the UK, agriculture was responsible for 10% of the total GHG emissions in 2016. The agricultural sector in the UK is the fifth largest contributor to GHG emissions. Other sectors like transport, energy supply, business and residential sector contribute most to the GHG due to higher CO_2 emissions. The Carbon dioxide was the dominating GHG in the UK which accounted for 81% of the total emissions followed by methane (11%) then nitrous oxide (4.5%) (DEFRA 2017b).

A variety of literature exists that focuses on reducing emissions from livestock farming. These studies consider changes in animal feed, manure management and storage, animal's health and fertiliser application that may lead to a reduction in methane and nitrous oxide emissions.

Moate, P. J. et al. (2017) conducted an experiment of 32 Holstein cows in Australia to measure the enteric methane production. They offered the dairy cows four different types of diets consisting of different portions of wheat, corn, and barley and alfalfa hay and then calculated methane emissions. They found that the methane emissions were significantly low when using a wheat based diet however it also leads to a reduction in milk-fat percentage and a reduction in the production of energy corrected milk[5].

Muñoz, C. et al. (2016) conducted a study to evaluate the enteric methane emission in 24 lactating Holstein cows by feeding them different herbage masses. They found that the cows which were fed low herbage mass pasture (LHM)[6] leads to an increase in milk production and a reduced amount of enteric methane emissions per unit of milk produced. These results were backed by O'Donovan, M. and Delaby, L. (2008) who found that feeding the dairy cows low herbage mass pasture leads to an increase in the production of milk.

The reduction in methane emissions cannot be only attributed to a change in the diet of an animal but also by managing the diseases. York, L. et al. (2017) found that by managing foot and mouth diseases in dairy animals in India, the methane production could be reduced. Other studies also suggested that maintaining animal health can have a positive effect in reducing methane emission and improving milk yield. The milk yield reduced to about 3.5% in Britain due to mastitis. The control of mastitis leads to an 8% decrease in UK dairy emission (Stott, A. et al. 2010).

A variety of studies have found that incorporating animals feed with high sugar grasses (HSG)[7] reduced the environmental footprint by decreasing nitrogen excreted through the animal urine while increasing milk production. Staerfl, S. M. et al. (2012) found that adding higher water soluble carbohydrate diet to the dairy cows reduced the nitrogen emission potential of the manure. Soteriades, A. D. et al. (2018) compared the conventional pasture with the HSG pasture. They found that the HSG pasture helped in reducing the emissions, especially when

[5] Energy needed to create a litre of milk is different depending on the content of fat and protein. ECM is a way to allow a fair comparison.

[6] Herbage mass is used to describe the quality of the pasture. It is the total amount of pasture calculated as dry matter per hectare (kg DM/ha)

[7] HSG are a new ryegrass variety specially bred to contain high levels of water soluble sugar which help to utilise more protein from the grass

combined with effective manure management practices. Furthermore, the use of HSGs increased milk production income and reduced manure management costs.

Di, H. J. and Cameron, K. C. (2002) investigated the effect of applying dicyandiamide[8] (DCD) to the soil to measure the reduction in the leaching of nitrogen into the soil from the dairy animal's urine. They found that the application of DCD to the soil decreased leaching by 76% in autumn and 42% in spring. Similarly, Monaghan, R. M. et al. (2013) found that the application of dicyandiamide (DCD) reduce N_2O emissions by 25% during winter and spring months.

The impacts of the GHG emissions are severe, and they need to be reduced, but it does not mean that we do not consume dairy or meat products. Some might argue that focus should be placed on exploring alternate sources of food. However, one can argue that finding an alternative source of food would be costly, and not just regarding money but also regarding time and energy. Furthermore, GHGs are still going to be emitted when producing any kinds of food especially when the agricultural process has not been refined through years of trial and error.

Even though livestock farming does contribute heavily to the GHG emission, we cannot stop producing livestock. A better option is to examine the inputs and use them in such a way that they produce less GHG. In the next few chapters, we would assess the efficiency of dairy farms in England and Wales and would take a closer look at the essential inputs in livestock farming.

2.4. Studies on sustainable intensification

There have been various estimates of the projected increase in the demand for global food in the future. Tilman, D. et al. (2011) projected that the demand for food would increase to 100% -110% by 2050. The increase in demand for food possesses the challenge of producing more food while managing the GHG emissions associated with it. They found that if the current trend of agricultural intensification continues in the richer nations and agricultural extensification continues in the poorer nations, then the global GHG emissions would increase significantly leading to major impact on the environment resulting in loss of ecosystem and extinction of

[8] Dicyandiamide is a nitrification inhibitor

species. However, if there is an increase in the global investment of technology, then the global food need by 2050 could be met with lower environmental impact.

Some argue that organic farms do have some of the qualities that are needed for sustainable agriculture (Rigby, D. and Cáceres, D. 2001). These farms have low yield per area so that they can reduce the use of land (Pretty, J. and Bharucha, Z. P. 2014). They reuse and recycle the farming inputs and outputs and their reliance on synthetic fertilisers and pesticides is minimal. Organic farms aim to maintain the fertility of the soil and biodiversity in the farm. These farms may be able to be classified under sustainable farms but they cannot be intensive farms as their output is low.

Kristensen, T. et al. (2011) estimated GHG emissions, as a proxy for sustainability, for conventional and organic commercial dairy farms. The milk yield was lower in organic farms and so was the emissions of nitrous oxide, however, the total GHG emissions per kg ECM milk were lowest in the conventional system. With the improvement in management systems and changes to the factors of production, organic farms may be able to achieve the stamp of being intensively sustainable.

Del Prado, A. et al. (2010)assessed the impact of different mitigating strategies for GHG emissions. Their mitigation strategy was related to the fertiliser, diet, management and genetic improvement on a typical dairy farm in the UK. Using these strategies, separately, they saw a decrease in GHG emissions however they argued that a single method of managing the emissions was not enough for a significant change.

Stott, K. J. and Gourley, C. J. P. (2016) argued that with intensification of the dairy sector in Australia, the loss of nitrogen to the environment is increasing and that it would be difficult to achieve the nitrogen efficiency through current grazing-based dairy farms.

So Styles, D. et al. (2017) used life cycle assessment (Silva, E. et al.) to evaluate the GHG effects from dairy and beef farms in the UK in a variety of scenarios. They considered the indirect GHG effects from an increase in crop production and replacement of suckler beef production due to the intensification of the farms. The GHG emissions increased due to intensification as the farms required more concentrated feed and maize. The GHG emissions reduced when the spared dairy grassland was used to intensify beef production with increasing afforestation on the lower quality grassland.

Cardoso, A. S. et al. (2016) evaluated the impact of intensification on beef production on the GHG emissions in Brazil. They compared different scenarios of increasing animal productivity using fertiliser, supplements and concentrated feed in beef production to determine which scenario may lead to a reduction in GHG. They found that intensification of the beef cattle led to a reduction in GHG emissions per kilogram of beef carcass. They added that changing from extensively grazed pasture to nitrogen fertilised improved pasture could potentially reduce emissions between one third to a half.

Caviglia-Harris, J. L. (2018) evaluated the changes in land use due to the intensification of beef and dairy in Brazil. They found that intensive dairy production required a smaller amount of pasture whereas the opposite was true for beef. Intensive dairy production reduced the demand for productive land whereas intensive beef production increased the demand for productive land. They concluded that intensifying dairy production would reduce deforestation hence reducing the emissions associated with deforestation.

Levers, C. et al. (2016) used crop yield and mineral nitrogen application in kilograms per hectare to identify agricultural intensification in Europe. They found that crop yield had increased in Europe whereas the Nitrogen application has decreased. The decrease in N application was a result of a variety of policies in Europe which focus on improving Nitrogen use efficiency.

2.4.1. <u>The case against Sustainable Intensification</u>

Many studies have been published that praise SI and believe that it is a way to protect and preserve our environment. However, there are a few studies that suggest that sustainable intensification might not be as good as it seems. There is certain criticism associated with this term. Some believe that sustainable intensification is just agricultural intensification whose focus is solely on the increase in production. They believe that sustainable intensification is going to be overshadowed by a need to increase the production of food. In the term sustainable intensification, much more weight is going to be given the term intensification as compared to the equal weight being given to the sustainable side (Garnett, T. and Godfray, C. 2012).

Most of the environmentalists view sustainable intensification as a threat. They believe that it refers to a specific type of agriculture where there is a high input which produces a high output. This changes the definition and understanding of SI. They believe that SI acts like a Trojan horse for support for genetically modified crops and biotech. Some argue that even if the food production has increased, it does not guarantee the reduction in hunger. They argue that eliminating hunger requires a structural change where the existing patterns of supply of food and the economic access to food are changed. In addition, some argue that changes need to be made to reduce the loss of food through waste rather than increasing the amount of food.

Those who are pro-SI argue that the need for SI is not just about increasing the quantity of food. It is about reducing the inputs while creating higher outputs with less negative impact on the environment. Secondly, the increase in productivity is going to depend on reduced food waste, improving governance, increasing yields and better supply chain management. Sustainable Intensification is essential for certain regions like sub- Saharan Africa where the economic driver is agriculture.

The trade-off between intensification and sustainably requires close attention as an increase in yields can negatively impact the potential of increased yield in the future due to resource exploitation (Smith, A. et al. 2017).

2.5. Conclusion

Increasing the production of food, although necessary with the rising population, exhibits certain constraints. An increase in food production through intensification can lead to environmental degradation especially when coupled with increasing fertiliser use. Secondly, increasing production by increasing the farmed area, by clearing land, degrades the environment though the loss of biodiversity and soil degradation.

So, an increase in food production while protecting the environment has been increasingly important. The concept of *"Sustainable Intensification"* was born which emphasises feeding world's population without hindering the potential ability of future generations to produce food. In this chapter, we explained the concept of sustainable intensification in detail and determined the need for SI in agriculture.

The next few chapters would use the concept of sustainable intensification defined in this chapter to assess the economic and environmental performance of dairy production in Wales and England.

3. AN OVERVIEW OF THE DAIRY SECTOR

3.1. Introduction

This chapter explores the recent trends in dairy farming in the UK and aims to provide an overview of the dairy industry. Dairy farming is the largest agricultural sector in the UK accounting for 17% of farm products by value (DEFRA 2015a). Dairy farming is a significant contributor to environmental degradation. This chapter aims to provide a summary of ways to improve the sustainability of dairy farms where the particular focus has been given to reducing GHG emissions associated with dairy farming.

The structure of this chapter is as follows. In section 2 we discuss how dairy farms operate with particular focus given to housing and grazing by the dairy cow. Section 3 explores the trends in dairy farming and discuss declining number of dairy producers. Section 4 reviews some regulations in place by the UK government to support dairy farming. Section 5 outlines some ways to improve the environmental sustainability of the dairy farms. Lastly, section 6 concludes the chapter.

3.2. Workings of a dairy farm

This section of this chapter provides an overview on the workings of a dairy farm in the UK.

3.2.1. <u>Birthing and lactation</u>

Dairy farming has been a part of agriculture for thousands of years. Dairy cows are explicitly bred to produce large quantities of milk. Dairy cows are required to birth one calf annually so that they can produce milk for ten months a year. An average dairy cow can start giving birth at 2 to 3 years of age so they may give birth 2 to 4 times in a lifetime.

The dairy cows have to give birth to produce milk so the dairy cows are in a constant cycle of pregnancy and birth so that they will continue to lactate. The cows are artificially inseminated within three months of giving birth. A pregnant cow is separated from the milking herd about two months before they give birth as they require a dry, clean and secluded place to give birth. The calves are removed from their mothers between a few hours to two days after they are born to obtain the maximum amount of milk.

Dairy cows often can only produce high milk yield for an average of three years. When the cow stops lactating or stops producing enough milk to be profitable, they are slaughtered for meat. The lactation cycle is the period between one calving and the next. The cycle is split into four phases, the early, mid and late lactation and the dry period. The early, mid and late lactation period lasts for 120 days each whereas the dry period lasts for 65 days. After calving a cow may start to produce 10kg of milk per day which increases to 20kgs per day 7 weeks after calving. By the end of the lactation period, milk yield reduces to 5 kg per day.

3.2.2. Housing and grazing

For the housing system to meet a cow's need, it is necessary to understand their behaviours. A housing system on the dairy farm must provide:

- A comfortable and well-drained laying area for cows
- A shelter from bad weather
- Adequate space for animals to move, lie in and rest freely
- Access to food and water

It is very important to provide adequate space for dairy cows to socialise and move around freely. This is especially necessary for farms with high stocking rates. It takes anywhere between 3 to 7 days to establish a social hierarchy amongst cows. The more limited space is, the less chnace an animal has to avoid unfavourable conditions. So, adequate space should be provided so that a subordinate cow can move away from the dominant one. According to British standards a loafing area of $3.0m^2$ per cow must be provided. Loafing area is an area which the cow uses for behaviour other than feeding or lying. A cow needs to be housed where there is an adequate supply of water as a cow requires 60 litres of water per day which can increase to 100 litres per day per cow depending on the milk yield. Since cows tend to drink in groups, adequate space should be provided to ensure good access to water supply for all.

The housing of the cows depends on the weather conditions. In the areas with a milder climate, the grazing period is longer whereas in an area where the weather is colder and rains are frequent, the cows are housed indoors for longer periods. In the UK, there are several different management systems being practiced with regards to the housing of the dairy cows given by ADHB (2018e).

- **Year- round housing:**

In year- round housing or continuous housing, the cows are kept indoors throughout the year. Continuous housing allows the farmer to develop a feeding strategy that may lead to increased milk yields. This method is common in areas where grass is in short supply due to adverse weather or soil conditions. Continuous housing is also practiced on farms with large herd size. Larger herds allow for the cows to be grouped together so that their needs can be met.

In the UK, approximately 5% of the dairy herd is housed throughout the year.

- **Seasonal housing**

This is the traditional system which is most commonly used in the UK. The cows are housed during autumn and winter season and can graze freely on the pasture during spring and summer season. The seasonal housing of animals is greatly supported by the British climate which is warm, wet and suitable for growing grass.

- **Zero grazing**

This is a pasture management system widely used in the areas where grass is not easily accessible. The grass is cut and fed to the animals indoors.

- **Grass based system**

In this system, the cows graze from the pasture from early February to late November. The cows maybe be housed indoors for the remainder of the year or they may be out-wintered if the field and weather conditions are suitable.

- **Woodchip pads**

In this system, the field is lined with woodchip corrals. This provides the farmer with an economic benefit of housing animals during winter compared to the conventional housing systems. Woodchip pads also provide other benefits that include improved animal health, less damage to pasture and reduced labour costs. The drainage from corrals will contain a high concentration of ammonia, phosphate and faecal material which poses a higher risk to the water environment. Thus the pads need to be appropriately designed and drained to mitigate the risk of water pollution (ADHB 2016).

Many of these management systems are often mixed with the majority of the systems providing shelter and housing for cows during the winter season. Mostly dairy cows are kept inside for part or all the year. Cows that are housed inside would have less opportunity to exercise while in-doors compared to the cows that are left on the pasture.

The natural environment for cattle is pasture. Pasture allows the cows to express normal behaviour and provides plenty of space for them to lie down and stretch. Pasture is also a cheap source of nutrition for cows. It is generally assumed that pasture is better for animal welfare compared to indoor housing systems. However, with the domestication of dairy cattle and selective breeding, the cows now have a higher nutritional requirement which cannot be fulfilled by pasture alone. This can lead to the cow being hungry and adversely affect an animal's health (Charlton, G. L. et al. 2011).

However, indoor housing is necessary especially in the areas which are prone to bad weather conditions. The housing practice may change depending on the weather conditions. In extreme weathers, the farmer might decide to house the cows especially during the summers when the temperature is too hot and the growth of grass is minimal.

3.2.3. Animal Health

Animal health and welfare has been an important aspect of dairy reforms. Measures have been put in place by the government to safeguard and protect the animals. With the introduction of CAP by the European Union, reforms were placed on the way that the animals are kept and managed. These reforms ensure that the farmers, traders and dealers understand the physical and welfare needs of the animals and that they should be able to recognise the sign of disease and be able to notify concerning bodies.

In the UK, Farm Animal Welfare Council is an independent government body that was formed to advocate and address issues concerning animal welfare. They came up with five freedom points to protect animals (DEFRA 2004):

- Freedom from hunger and thirst
- Freedom from discomfort
- Freedom from pain injury and suffering

- Freedom to express normal behaviours
- Freedom from fears and distress

3.2.4. The production of milk

Up until the mid-20th century, dairy cows were milked by hand. But now milking machines are widely used. Milking machines allow the farmers to milk more cows in a short period of time as milking is considered as the most labourious and time-consuming activity on the farm (Aslam, N. et al. 2014). Generally, cows are milked twice a day. There are studies that support milking cow three times a day to produce higher yields (Erdman, R. A. and Varner, M. 1995; Aslam, N. et al. 2014) and lower the incidents of mastitis, however, the extra cost of labour, electricity and machinery sometimes does not make it worth while (ADHB 2018b).

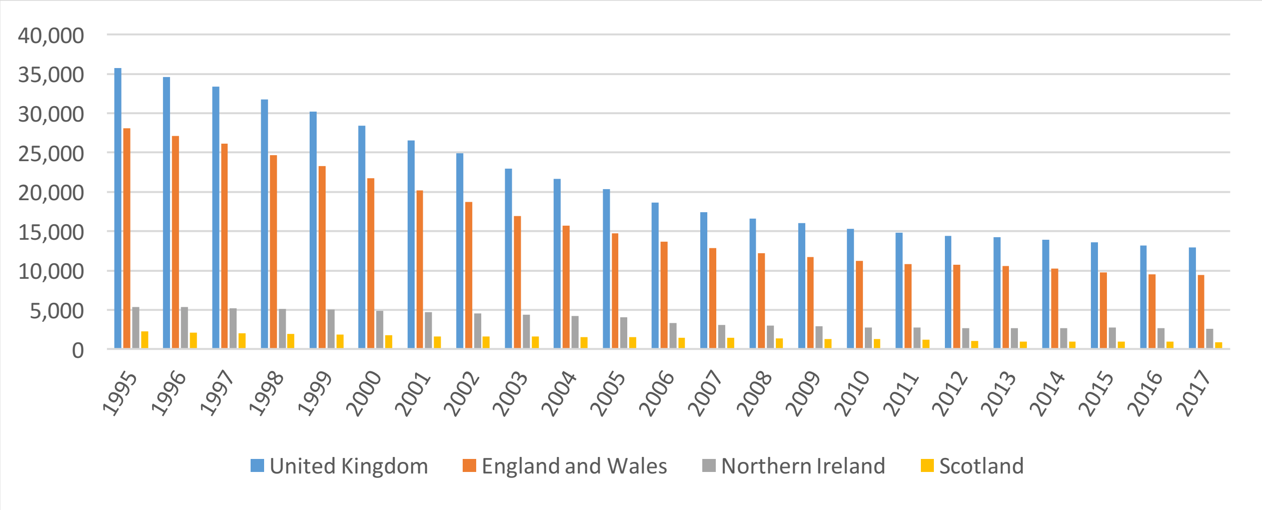
Dairy farming is becoming more intensive to increase the amount of milk produced per cow. The Holstein-Friesian is the most common type of dairy cow in the UK, Europe and the USA. These cows have been bred to produce very high milk yield. Average milk yield per cow in the UK is 22 litres per day with some cows even producing 60 litres a day during peak lactation periods.

3.3. *Structure of the dairy industry*

This section of the chapter explores some structural variables of dairy farming like producer number and the number of dairy cows in the UK. The dairy producer numbers in the UK, England and Wales, Northern Ireland and Scotland are presented in Figure 3.1.

The dairy producers in the UK are decreasing. In 1995, there were 35,741 dairy producers in the UK which have declined to 12,960 producers by 2017. So, over a period of 22 years, the UK has seen a 64% decline in the number of dairy producers. In the year 1995, there were 28,093 dairy holdings in Wales and England however by 2017, the number of dairy producers has declined to 9,410 in Wales and England. So, over the course of 22 years, there has been a 65% decline in the number of dairy producers in Wales and England.

Figure 3. 1: Dairy Producer Numbers in the UK (1995-2017)[9]



Source: ADHB (2018g)

Northern Ireland producer numbers declined 51% and the producers' number in Scotland declined 59%. The number of dairy producers declined quite rapidly from 1995 to 2007 which saw producer numbers being reduced to almost half of what they were in 1995. The decline in producer number in the dairy sector is not unique to the UK. Other major dairy producing countries like Canada, US and the EU-25 also has seen a decline in producer numbers (DairyCo 2013). The decline in the number of producers is due to economic and social factors. The economic factors like business profitability and cost level are found to affect the producer numbers while the social factors like the presence of a successor, legislations and milk contract affected a farmers decision to stay in the dairy sector (DairyCo 2013).

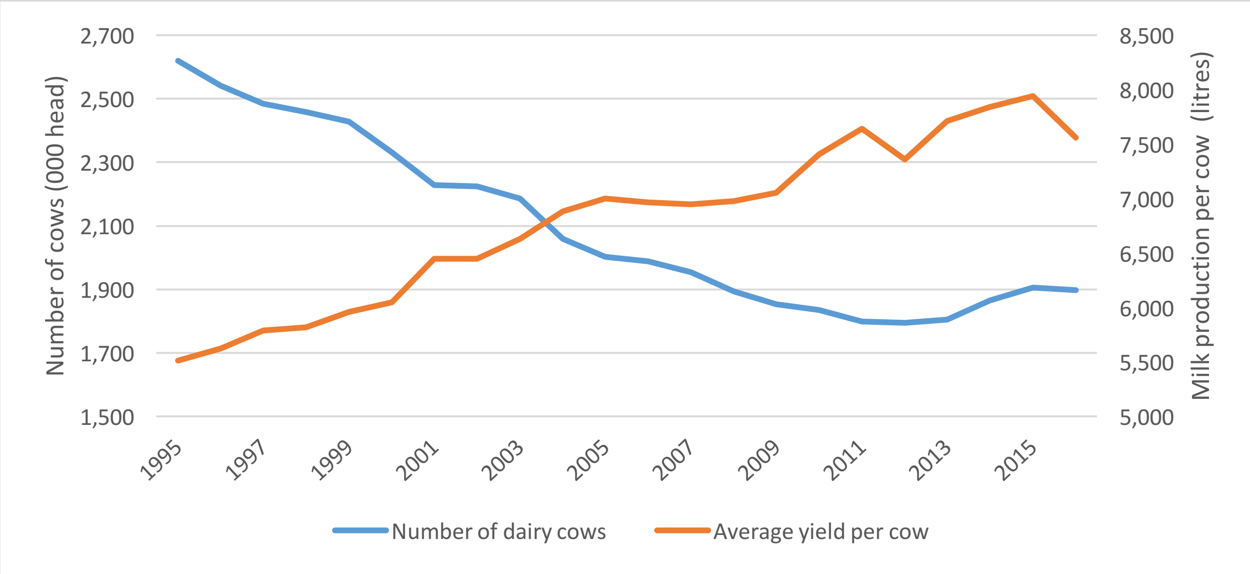
With the decline in the number of milk producers over the years, the number of dairy cows in the UK are also declining. However, the decline in cow numbers is far less than the decline in the producer numbers. The number of dairy cows in the UK declined from 1,619 million head in 1995 to 1,898 million head in 2016. So, over the course of 21 years, we saw a 28% decline in the number of dairy cows in the UK.

With the decline in the dairy producer numbers and the number of dairy cows in the UK, we would expect that the total milk production would also decline. However, the total milk production in the UK has remained relatively unchanged despite the cow numbers decreasing

[9] The dairy producer numbers in the UK, Wales, England, Northern Ireland and Scotland are provided in the Appendix 3.1

27% from 1995-2016. The total milk production has barely declined 1% over the same period. The reason is that the cows are becoming more productive. This is seen in Figure 3.2 where we plot the number of cows and an average milk yield per cow from 1995-2016.

Figure 3. 2: The number of cows and average milk yield per cow (1995-2016)

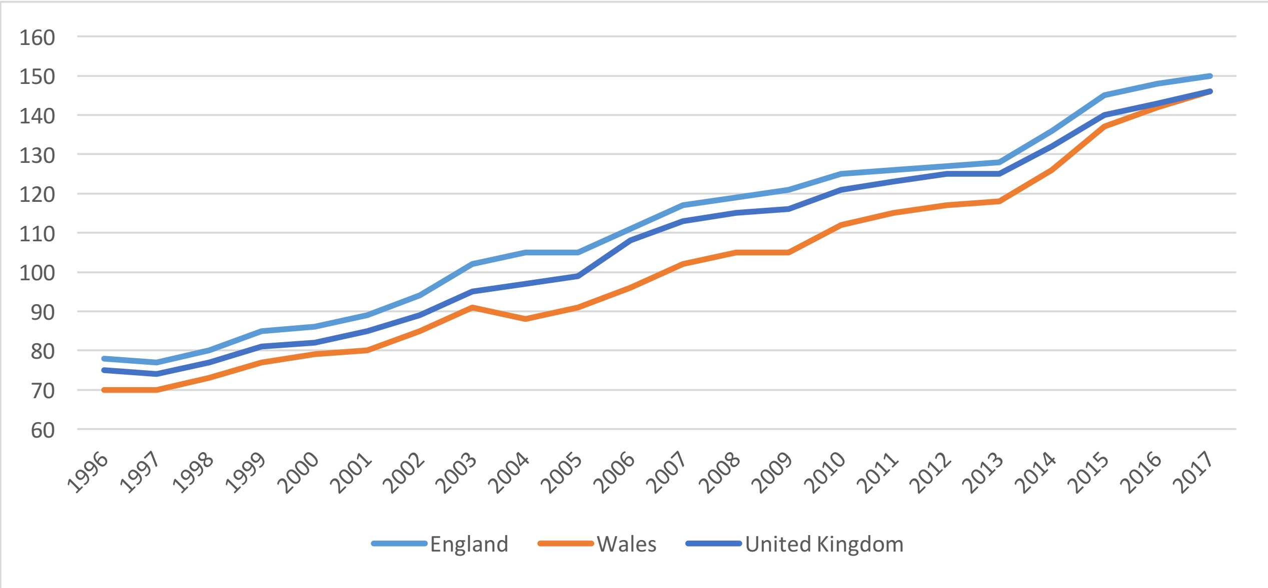


Source: ADHB (2017)

We can see that the number of cows is declining whereas the milk production per cow has risen. The increase in milk production per cow is due to improvement in technology, the increase in milking of a cow per day (Erdman, R. A. and Varner, M. 1995; Aslam, N. et al. 2014) , selective breeding (Stafford, K. J. and Gregory, N. G. 2008) and animal genetics (VandeHaar, M. J. et al. 2016).

With a 62% decline in dairy producers in the UK but only a 27% decline in the number of cows, the herd size on UK farms is increasing. The average herd size in the UK, Wales and England is plotted in Figure 3.3.

Figure 3. 3: Average herd size, UK, Wales and England (1996-2017)



Source: ADHB (2018a)

The average herd size on a UK farm has increased from 75 cows in 1996 to 146 cows in 2017, showing a 95% increase in a dairy herd. Similarly, an increase in herd size in England and Wales is also observed. The herd size in England increased from 78 cows in 1996 to 150 cows in 2017 whereas the herd size in Welsh farms increased from 70 cows in 1996 to 146 cows by 2017. So, a dairy farm in England saw an 80% increase in herd size while the dairy farms in Wales saw a 108% increase in the herd size over the period of 22 years.

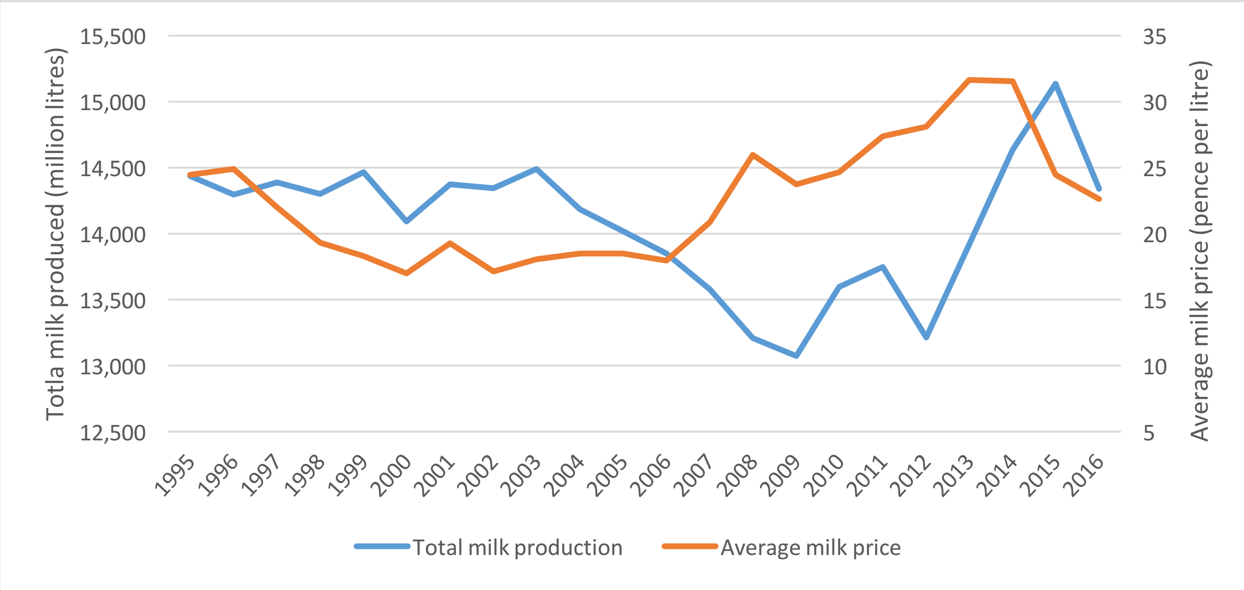
The average herd size and milk yield per cow is increasing. The production is concentrated to fewer but larger farms resulting in a decrease in the number of farms but an increase in milk production. Thus, dairy farming in the UK is becoming more intensive and specialised. The trends in dairy production are driven by economic and social factors. Increasing demand for dairy products, technological changes and price support had also led to farms becoming more intensive.

3.3.1. Dairy farms profitability

Milk prices are the backbone of a farm's profitability and changes in milk prices has had a significant effect on a farm's profits. The average milk production and price of milk per litre is plotted in Figure 3.4.

The price of milk per litre has remained relatively unchanged over the years. The average milk price and total milk production are negatively correlated with each other. An increase in milk supply drives the price of milk down whereas a decline in the production of milk increases the prices due to lack of supply and relatively constant demand.

Figure 3. 4: The average milk price per litre (1995-2016)[10]



Source: ADHB (2017,2018h)

In 2016, the estimated cost of production varied between 25 to 30 pence per litre and the average farm gate price of milk was 19.02 pence per litre. After subsidies and grants, the average farm gate milk price rose to 25.57 pence per litre (Downing, E. 2016). So the farmers are unable to cover the cost of production without subsidies or grants (Downing, E. 2016). Many small dairy farms have had gone out of business due to the high cost of production (Perry, M. 2015).

3.3.2. <u>Rising feed prices</u>

Food prices have been rising since 2002 due to the contribution of various factors such as rising production of biofuel from cereals and grains, the weak dollar and the increase in the food production cost due to rising energy prices. The agricultural commodities market is highly

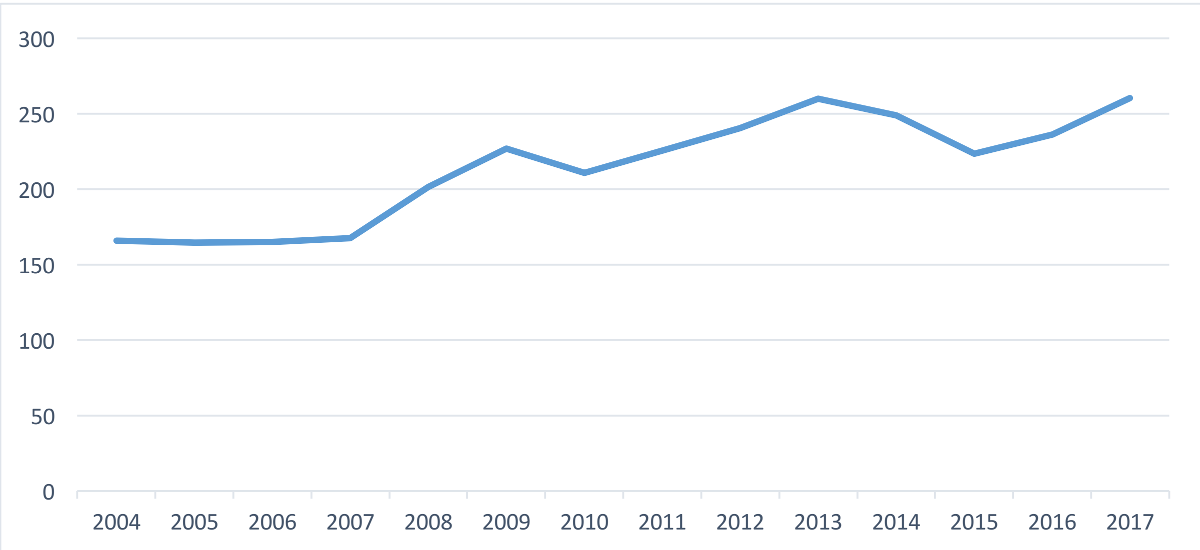
[10] Not adjusted for inflation

volatile and the UK production is vulnerable to the world's price fluctuations (Schoen, V. and Lang, T. 2014)

Mitchell, D. (2008) found that the increasing biofuel production in the US and the EU has been a major contributing factor to the increase in global food prices. He argued that with the increase in biofuel production, the global wheat and maize stocks would not have declined and so the adverse weather conditions would not have affected the production or the costs much if the dependence on wheat and maize due to biofuel production was not so high. Globally, we saw a 56% increase in IMF's index of internationally traded food commodity prices from January 2007 to June 2008.

A global increase in food prices (wheat, maize and other crops) also affected the prices of animal feed and vice versa. The average cost of feed per tonne is presented in Figure 3.5 from 2004-2017.

Figure 3. 5: Feed costs per tonnes (2004-2017)



Source: ADHB (2018d)

All feed costs have been adjusted for inflation at 2015 price level. Over the years, we can see that the cost of feed per tonne has been rising. In 2004, the cost of feed per tonne was £166. The cost of feed remained steady till 2007 when the cost of feed averaged around £168 per tonne. However, the costs rose 20% in 2008 to £201 per tonnes. The trend in increasing prices continued till 2009 when the average cost rose to £227 per tonne. The price fell to £211 per tonne in 2010 but the decline in prices was not for long as in the following years, the cost of feed per tonne rose to £260 per tonne in 2013. The cost per tonne fell slightly by 2015 but then rose again to 2013's level by 2017.

The rising feed prices are a result of poor harvest and increasing demand from fast-developing counties. Hot weather affected most parts of Europe in 2006 which led to a decrease in the production of animal feed in the next year. Rising demand by India and China coupled with the poor harvest, saw a rise in prices starting in 2007. Furthermore, the 2007 harvest was affected in the UK by wet weather during June and July which had a negative effect on the quality and the quantity of the feed being produced (BPEX 2007).

The weather conditions together with increasing demand of wheat and maize, globally lead to an increase in feed prices by 2009. The price of wheat and maize began to increase in the last quarter of 2010 due to the wheat crop damage in Russia, poor growing conditions in the US and a weakening of the dollar (FAO 2011). The increase in feed prices continued until 2013. The price of feed fell in 2014 and 2015 due to a decline in price of wheat (AHDB 2016). The global food prices dropped 14% between August 2014 and May 2015 due to an increase in the harvest of wheat, maize and rice and low cost of oil (TheWorldBank 2015).

With the increase in wheat and barley prices, the cost of feed per tonne has started to increase in 2016. It is projected that the cost of feed will continue to rise in 2018 with large effects seen in 2019 due to a prolonged heat wave in the UK which resulted in the loss of grass and forage (BBC 2018).

3.4. Regulations

The British livestock industry has changed a lot due to reforms of Common Agricultural Policy (CAP). The Common Agricultural Policy (CAP) is the EU policy to provide financial support to farmers. Approximately 40% or €58 billion of the total EU's budget has been allocated for CAP. The main goal of CAP is to safeguard and protect farmers form volatile agricultural prices and to provide food security. The objectives of CAP are:

- To increase agricultural productivity by ensuring optimum use of inputs
- To ensure fair standard of living for the farmers
- To stabilise markets

- To ensure reasonable priced products for the consumers.

So, CAP provides income support to farmers by supporting the prices they were paid for produce. The support provided through CAP is two folds. Firstly, there are direct payment which are according to the farm area and second is rural payments which are smaller in size and for rural development.

Farmers in the UK are subjected to greening rules which ensure that farms are sustainable. The greening rules ensure a farms' commitment to biodiversity and climate change. Under greening rules, approximately 30% of the direct payment are given to the farms is linked to crop diversification, maintaining permanent grassland and contributing 5% of arable area for environmental friendly measures.

CAP has been widely criticized as a system that promotes and encourages overproduction of produce which is then alter on dumped into the third markets where it impacts their local agriculture.

However, with Brexit, UK will have the opportunity to implement policies that may counter the criticism on CAP. Agricultural policies need to:

- Encourage efficient production which contributes positively to the economy.
- Contribute to the reduction in GHG emissions and improve biodiversity.
- Can fulfil consumers' need through the availability of nutritious food and reasonable prices.

3.4.1. Support measures

There are no quick fixes to improve dairy farm profitability but government actions have regularly helped farmers stay in business. Government support packages are one of the reasons many farmers do not exit the market even though dairy farming is not as profitable as other sources of employment. Some recent schemes and programs to boost farm productivity and profitability are listed below.

- One-off support payment of £26.2 million was made to dairy farmers in the UK in 2015 to help with their cash flow problems. England received £15.5 million, Wales £3.2 million, Northern Ireland £5.1 million and Scotland £2.3 million. The one-off payment for an average size farm in England and Wales received £1,800 per farm while Northern Irish farms received £2000 and Scottish dairy farms received £2,500 (DEFRA 2015b).

- In 2017, £120 million were allocated to the Rural Development Programme for England – Growth Programme for farmers who were looking to diversify their activities. The grant was introduced to boost tourism to farms across the country and for a business that wanted to diversify into non-agricultural activities (DEFRA 2017a).
- In 2018, £60 million farming productivity fund was launched where the farmers could bid for cash to buy new farm equipment. Farmers could apply for a grant of £3,000 to £12,000 towards the cost of farming equipment. This grant was put forward as a measure to improve the competitiveness of dairy farmers and to make them more resilient to change especially in the wake of UK leaving the EU (DEFRA 2018a).
- A £7.3 million package was announced for Welsh farms which were EU backed. The funds were provided to boost the food sector in Wales (Government, W. 2018).

3.5. Improving sustainable intensification of dairy farms

The concept of sustainable intensification has been explored in detail in Chapter 2. For this thesis, the environmental sustainability is determined by the emissions of the GHGs from dairy production systems.

In the UK, GHG emissions are dominated by carbon dioxide (CO_2) which makes up 81% of the total GHG emissions. Methane (CH_4) emissions account for 11%, nitrous oxide (N_2O) emissions account for 5% and the remaining 3% are due to the fluorinated gases in 2016 (DEFRA 2018b). The emissions of carbon dioxide, methane and nitrous oxide have been reducing in the UK over the years. The trend in the UK's GHG emissions is presented in Table 3.1.

Table 3. 1: UK GHG emission trends by gas (1990-2016)

	1990	2000	2010	2016
CO_2 (Mt CO_2 eq)	594.1	553.7	492.7	378.9
CH_4 (Mt CO_2 eq)	133.2	109.1	64.5	51.6
N_2O (Mt CO_2 eq)	49.6	29.9	22.5	21.4
Rest (Mt CO_2 eq)	17.3	12.3	17.4	16
Total GHGs(Mt CO_2 eq)	794.2	705.0	597.1	467.9

Source: DEFRA (2018b)

The emissions have been decreasing over the years. The CO_2 emissions declined 36% from 1990 to 2016. The decline in CO_2 emissions is a result of a reduction in emission from power stations due to declining use of coal. The CH_4 emissions decreased by 61% and N_2O emissions fell 57% from 1990 to 2016. Overall, the GHG emissions in the UK have declined from 794.2 Mt CO_2 equivalents in 1990 to 467.9 Mt CO_2 equivalents in 2016. So, over the period of 26 years, the GHG emission in the UK have declined 41%. The decline in emission is a result of changing policies at not just national but at international level. To combat climate change and to reduce GHG emissions a variety of national and international agreements have been made.

In 1992, The United Nations Framework Convention on Climate Change (UNFCCC) was introduced whose object was to "stabilise greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (UNCED 1992). Then in 1997, The Kyoto Protocol was introduced as an extension of UNDCCC. It is an international agreement under which the industrialised countries are legally obliged to reduce their combined GHG emissions by 5.2% from 1990 base year. Under the first commitment (2008-2012), the EU and member states committed to reducing the emission in the EU by 8% on 1990 levels by 2012. The UK contributes to this goal by reducing its emissions by 12.5% below 1990's level from 2008-2012. Under the second committed period (2013-2020) the EU and member states must reduce their emission by 20% relative to the base year 1990.

The UK has set its own domestic targets for reducing GHG emissions under The Climate Change Act 2008. Under this act, the UK has committed to reducing its GHG emissions by 80% below the 1990 base level by 2050 (DEFRA 2018b).

In the UK, agriculture contributed to 10% of the UK's GHG emissions in 2016. The agricultural sector is the largest contributors to CH_4 and N_2O emissions. The emissions from agriculture have decreased 16% from 1990 to 2016 due to the decline in the number of animals and the decline in the use of synthetic fertiliser (DEFRA 2018b).

The reduction in emission from the agricultural sector has been due to a number of factors which are discussed in this chapter.

3.5.1. Reduction of Ammonia though proper storage

Nitrogen in the form of ammonia is lost when manure meets air through the process of nitrification and denitrification. The covering of manure reduces its exposure to air and hence reduces the emissions of ammonia. The manure should be covered with plastic to reduce its exposure to air and to limit the odour emitted from it.

The slurry should be covered when stored or should be able to develop a natural crust. The farmers should ensure that they have enough storage to store the slurry and it should only be spread when the crops will use the nutrients. The slurry storage capacity should be calculated according to the area of the farmland. Furthermore, when fibre content is high in the slurry, it should be allowed to develop a natural crust. A natural crust reduces ammonia emission by up to 40%.

Apart from allowing the slurry to develop a natural crust, there are other methods to prevent slurry from being exposed to the air. Tight lid roof structures can be built on steel tanks and silos. They are highly effective in reducing the emissions during storage by around 80%. This method also helps to prevent rainfall from entering the tanks. Another method is of floating sheets that are placed on slurry tanks or small earth-banked lagoons. The covering sheet is usually made of plastic or canvas and can potentially reduce ammonia emissions by 60%.

3.5.2. Reducing emission through spreading organic manure

Ammonia is also emitted during the application of manure to the soil. Methods should be adopted to ensure that organic manure is spread according to the soil type, nutrients and crop needs to minimise the emissions of ammonia. The emissions of ammonia through the application of manure to the soil can be reduced by decreasing the surface area exposed to the air. The manure in the form of slurry could be placed beneath the soil surface using an injector which would limit the exposure to air.

Other methods such as trailing hose[11], trailing shoe[12] and injections are low emission spreading equipment. These methods place manure directly onto and into the soil so that the soil retains more nitrogen. This way less organic material can react with the air. Another method of

[11] Trailing hose is a type of manure spreading technique which has several hoses that distribute liquid manure close to the ground.
[12] Trailing shoe is a slurry applicator that can be fitted to any size tanks. The applicator has rake like bars that move forage aside and create shallow slits that help to absorb the nutrients.

application of manure to the soil is of a broadcast slurry. Broadcasting involves forcing liquid material at high pressure onto a plate that sprays it onto the air. The trailing hose can achieve a 30% to 35% reduction in ammonia emissions, and a trailing shoe can achieve 30-60% reduction in ammonia compared to the broadcast slurry. Injectors can achieve the highest reduction in ammonia emissions which can be up to 70% to 90%. Injectors are suitable for arable and grasslands however they should be avoided on the land with a drainage system to prevent water pollution.

The application of manure should be time appropriate. The emissions of ammonia almost double after a 5 °C increase in temperature. Wind speed also alters the emissions of ammonia. So, to reduce the emissions of ammonia, the manure should be spread under cool and windless conditions or when the wind speed and temperature is decreasing.

3.5.3. Increasing biodiversity

Dairy farming has a significant impact on the landscape of an area. Increasing pressure to generate revenue has led to an increase in the size of the farm. The larger farms have a larger herd size which requires more grazing area. Larger farms use grassland more intensely as they cut grass earlier and apply more fertilisers to achieve high milk yield. This has impacted the quality of soil and biodiversity on a farm. Biodiversity refers to all different plants, animal and insects on the farms.

Dairy farms can improve biodiversity by having a variety of crops which would provide habitat and shelter to different species. They can also enhance the biodiversity of a farm by having more trees and hedges. Reduction in the use of fertiliser has the potential to improve biodiversity.

Increasing biodiversity on a farm has a positive effect. An increase in biodiversity contributes to improving soil quality which facilitates productivity. It also prevents soil erosion and provides shelter to the animals from sun and winds.

3.6. Conclusion

In this chapter, we examined the workings of the dairy farms by reviewing the different aspects of a farm. Furthermore, the trend in dairy farming in the UK suggested that the number of producers is declining, but the herd size on a dairy farm has increased. The dairy cows are becoming more productive, i.e. they are producing more milk due to which the supply of milk has not decreased over the years despite the producer numbers declining 64% from 1995 to 2017. The decline in producer numbers has been linked to high input costs which have made dairy farming less profitable.

A variety of support measures has been in place to improve their cash flow. However, profitability is not the only problem the dairy farms pose. The dairy farming and agriculture, in general, has been linked to having a negative impact on the environment. A variety of methods were also discussed that could potentially help reduce emissions from the dairy.

3.7. *Appendix*

Appendix 3. 1: Dairy Producer Numbers for the UK (1995-2017)

	United Kingdom	England and Wales	Wales	England	Northern Ireland	Scotland
1995	35,741	28,093			5,409	2,239
1996	34,570	27,092			5,343	2,135
1997	33,352	26,110			5,233	2,009
1998	31,753	24,681			5,121	1,951
1999	30,221	23,286			5,039	1,896
2000	28,422	21,772			4,855	1,795
2001	26,556	20,191			4,741	1,624
2002	24,930	18,695			4,596	1,639
2003	22,992	16,943	2,946	13,998	4,425	1,590
2004	21,616	15,750	2,774	12,977	4,201	1,569
2005	20,313	14,707	2,614	12,093	4,058	1,523
2006	18,626	13,675	2,441	11,234	3,376	1,472
2007	17,427	12,853	2,294	10,559	3,129	1,431
2008	16,592	12,212	2,172	10,040	2,989	1,351
2009	16,008	11,715	2,093	9,622	2,967	1,298
2010	15,300	11,251	1,987	9,264	2,781	1,263
2011	14,793	10,866	1,925	8,941	2,753	1,189
2012	14,413	10,712	1,902	8,809	2,662	1,027
2013	14,276	10,567	1,888	8,680	2,684	1,011
2014	13,922	10,232	1,847	8,385	2,655	993
2015	13,570	9,791	1,791	8,000	2,742	1,001
2016	13,227	9,554	1,751	7,804	2,694	974
2017	12,960	9,410	1,729	7,681	2,636	918

Source: ADHB (2018g)

4. METHODOLOGY

4.1. Introduction

This chapter outlines the theoretical framework used for the estimation of efficiency and productivity. The performance measurement of a firm is done as a relative measure either across the industry or across time. The performance of a firm is either measured as productivity or efficiency. Both concepts are reviewed in this chapter.

Since this thesis is about measuring the efficiency of farms, we explored the parametric and non-parametric methods of estimating efficiency in detail. The parametric methods of estimating efficiency involve an estimating of the production function through either Cobb Douglas or Translog functional forms. The efficiency is measured through linear regressions like Ordinary Least Square (Nicholson, F. et al.) and Corrected Ordinary Least Square (COLS) or through Stochastic Frontier Analysis. The non-parametric method of estimating efficiency does not require a production function. The non-parametric method of calculating efficiency is known as Data Envelopment Analysis (DEA). All these measures are explored in detail in this chapter to help us determine the best possible methodology for estimating efficiency.

The structure of this chapter is as follows. Section 2 explores the theory behind estimating of efficiency. In section 3 we discuss efficiency and productivity. Then section 4 examines economic efficiency which considers input and output price data. Sections 5 and 6 present the parametric and non-parametric methods of estimating efficiency, respectively. In section 7 we explored literature that compares DEA with SFA to determine which method is more appropriate for this study. Lastly, section 8 concludes the chapter.

4.2. Theory of efficiency

Consider a firm that uses *N* amount of inputs like land or labour to produce a single output. The technology possibility of a firm can be described as:

$$q = f(x) \tag{4.1}$$

Where q is the output and $x=(x_1, x_2, \ldots, x_N)'$ is a Nx1 vector of inputs. There are certain properties associated with the production function (Coelli, T. J. et al. 2005):

1. Non-negativity:The value of $f(x)$ is finite and non- negative.

2. Weak Essentiality**:** The production of output cannot occur with the use of an input
3. Non-decreasing in x**:** An additional unit of input would not decrease the output. More formally, if $x^0 \geq x^1$ then $f(x^0) \geq f(x^1)$.
4. Concave in x**:** Any linear combination of the vectors x^0 and x^1 will produce an output that is no less than the same linear combination of $f(x^0)$ and $f(x^1)$. Formally, $f(\theta x^0+(1-\theta)x^1) \geq \theta f(x^0)+(1-\theta)f(x^1)$ for all $0 \leq \theta \leq 1$. The concavity implies that all marginal products are non-increasing.

These properties are not always maintained as productions vary from industry to industry. For example, the assumption of non-decreasing x can be relaxed when additional inputs can obstruct the output. The above case for a firm that uses a single input to create a single output.

We can modify the above production function to work for multiple inputs that generate multiple outputs. The multiple input to multiple output process will thereafter be mentioned as production technology. Consider an input vector $x=(x_1, x_2, \ldots., x_J)$ which is used to produce an output vector $y=(y_1, y_2, \ldots.y_R)$ the technology set is defined as:

$$T = \{(x, y) | x \; can \; produce \; y\} \tag{4.2}$$

The set contains all input-output vectors (x, y) such that x can produce q.

The production technology defined by set T, can be represented as an output or an input set.

The output set is defined as, $P(x)$ which represents the set of all output vectors y, that are produced using the input vector x. The output set, $P(x)$ is defined by:

$$P(x) = \{q: x \; can \; produce \; y\} = \{y: (x, y) \in T\} \tag{4.3}$$

The properties of output can be summarized as follows. For each x, the output set $P(x)$ has to satisfy:

1. $0 \in P(x)$: nothing can be produced from a given set of inputs

2. Non-zero output level cannot be produced from zero levels of inputs

3. $P(x)$ satisfies strong disposability of outputs: if $y \in P(x)$ and $y^* \leq y$ then $y^* \in P(x)$

4. $P(x)$ satisfies strong disposability of inputs: if y can be produced from x then y can be produced from any $x^* \geq x$

5. *P(x)* is closed

6. *P(x)* is bounded

7. *P(x)* is convex

The production technology *T* when represented as an input set *L(Y)* consists of all inputs x that can produce a given vector y.

$$L(y) = \{x: x\ can\ produce\ y\} = \{x: (x, y) \in T\} \tag{4.4}$$

The input set consist of all input vectors *x* that can produce a given output vector *y*. The following properties of the input set can be derived.

1. *L(y)* is closed for all *y*

2. *L(y)* is convex for all *y*

3. Inputs are said to be weakly disposable if $x \in L(y)$ then for all $\lambda \geq 1$, $\lambda x \in L(y)$

4. Inputs are said to be strongly disposable if $x \in L(y)$ and if $x^* \geq x$ then $x^* \in L(y)$

Using the production possibility set Farrell, M. J. (1957) measures technical efficiency by radial reduction in inputs to produce a given level of output while remaining in the feasible set. The reduction in inputs while keeping the level of outputs the same is known as input oriented technical efficiency which can be defined as:

$$\theta_n = \min\{\theta | \theta x \in L(y)\} \tag{4.5}$$

Where θ is the proportional reduction of inputs.

The technical efficiency can also be measured under output orientation where there is a radial expansion of outputs while using the same level as inputs. The output oriented technical efficiency is defined as:

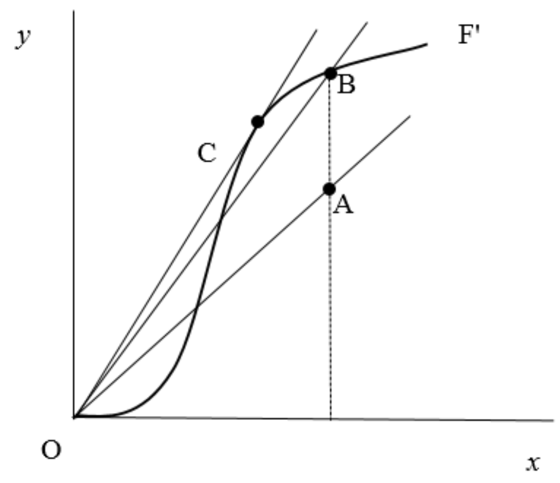
$$\phi_n = \max\{\phi | \phi y \in P(x)\} \tag{4.6}$$

Where ϕ is the proportion of expansion of outputs.

4.3. Efficiency or productivity?

The terms efficiency and productivity have been used interchangeably however they are not the same thing. To illustrate the difference between efficiency and productivity, we consider a simple production process in which a single input *(x)* produces a single output *(y)* as shown in Figure 4.1.

Figure 4. 1: Productivity and technical efficiency



Source: Coelli, T. J. et al. (2005)

The line *OF'* represents the production frontier that defines a relationship between inputs and outputs. The production frontier represents the maximum output that could be achieved from the inputs. So, the production frontier reflects the state of technology in the industry.

The firms that operate on the production frontier are labelled as technically efficient and if they operate under the frontier then they are technically inefficient. Point *A* represents a technically inefficient firm that lies below the frontier and both points *B* and *C* lie on the frontier so they are technically efficient. The firm *A* is technically inefficient as it can increase its output to the level of firm *B* without requiring any additional inputs.

To show the difference between productivity and efficiency, we can look at the slope of the line intersecting *O* and a particular data point *(A, B* or *C).* The slope of the line is then defined as *y/x* and provides the measure of productivity. If the firm *A* moves to the data point of firm *B*, the slope would be greater and hence firm *A* would increase its productivity. If the firm *A* moves to point *C*, then the line would be tangent to the production frontier and hence would define the maximum possible productivity. The point *C* is the optimal scale and the operations at any other points on the production frontier would lead to lower levels of productivity.

So, the firms that are technically efficient, like firm *B*, may be able to improve their productivity by changing the scale of their operations.

4.4. Economic Efficiency

In the above section, technical efficiency was described using inputs to create outputs. The efficiency can either be input oriented or output oriented. The input oriented technical efficiency of a producer is calculated as a ratio of observed inputs and the minimum potential inputs that could be used to produce the same level of outputs. The output oriented technical efficiency is measured as a ratio of observed output and the maximum possible output that could potentially be achieved through the use of same level of inputs.

However, the producer's decision to use inputs to create outputs depends on the input and output process. Economic efficiency can be measure by utilising the input and output price data. Economic efficiency can help to measure cost and revenue efficiency.

The cost efficiency aims to minimise the costs given the input price level and so is measured as a ratio of minimum feasible costs to actual costs. The revenue efficiency of a firm aims to maximise the revenue given the output prices and so is measured as the ratio of maximum feasible revenue and actual revenue.

This section describes the underlying theory behind cost and revenue efficiency.

4.4.1. Cost Efficiency

Consider a case where a firm uses multiple inputs to produce an output. If the data for input prices is available then the cost efficiency can be estimated. Commonly the size of a firm is relatively small so they have little influence on the input prices. These firms must take input prices according to market rate. The cost minimizing problem of a firm is written as:

$$c(w, q) = \min_{x} w'x \tag{4.7}$$

St: $$T(q,x) = 0$$

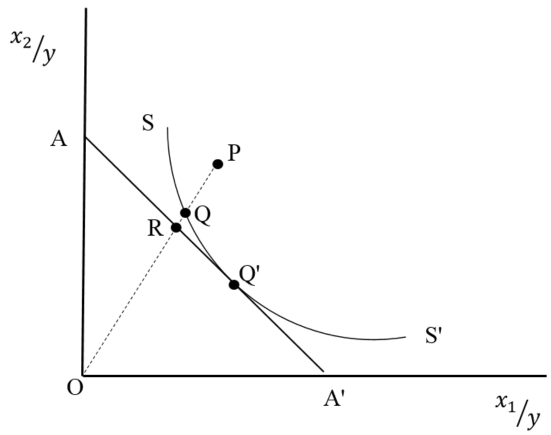
Where $w = (w_1, w_2, \dots, w_N)'$ is a vector of input prices, q is the output quantity and x is the input quantity. Cost function needs to satisfy the following properties (Coelli, T. J. et al. 2005):

1. Non-negativity: Costs can never be negative
2. Non-decreasing in *w*: An increase in input prices would not decrease costs.
3. Non-decreasing in q: It would cost more to produce more output
4. Homogeneity: Multiplying all input prices by an amount *k>0* will cause a k-fold increase in costs.
5. Concave in *w*

Following Coelli, T. J. et al. (2005) and Farrell, M. J. (1957) we need to first look at input-oriented measures to understand cost efficiency. Suppose that a firm uses two inputs (x_1 and x_2) to produce one output (*y*) under the assumption of constant returns to scale. Isoquant of technically efficient firms are represented by SS' which measures technical efficiency in Figure 4.2

Point P defines firm's input quantities used to produce an output. Since that firm does not lay on the frontier *SS'*, it is an inefficient firm. Then the distance *QP* represents a measure of technical inefficiency. *QP* is the amount by which all inputs could be proportionally reduced without a reduction in output. This is expressed in percentage terms by the ratio *QP/OP* which represents the percentage by which all inputs must be reduced for the firm to be technically efficient.

Figure 4. 2: Input-orientation Efficiency Measures (technical, allocative and cost efficiency)



Source: Coelli, T. J. et al. (2005)

The technical efficiency of a firm is the ratio:

$$TE = \frac{OQ}{OP} \tag{4.8}$$

Which is equal to *1-QP/OP*. TE takes a value between 0 and 1. A value of 1 implies a fully efficient firm which lies on the frontier like point *Q*.

Suppose that *w* is a vector of input prices and *x* is the vector of input quantities associated with point P. Let $\hat{x}$ and x^* represent input vectors associated with technically efficient point *Q* and the cost – minimizing input vector at *Q',* respectively. The cost efficiency of the firm can be defined as a ratio of input costs associated with input vectors x and x^*. Thus,

$$CE = \frac{w'x^*}{w'x} = \frac{OR}{OP} \tag{4.9}$$

If the input price ratio represented by slope of isocost line AA' is known, then allocative efficiency and technical efficiency can be calculated by using formulas:

$$AE = \frac{w'x^*}{w'\hat{x}} = \frac{OR}{OQ} \tag{4.10}$$

$$TE = \frac{w'\hat{x}}{w'x} = \frac{OQ}{OP} \tag{4.11}$$

The distance RQ represents reduction in production costs that would occur if production would occur at technically and allocative efficient point Q' rather than point Q. Then overall cost efficiency can be expressed as product of technical and allocative efficiencies.

$$TExAE = \left(\frac{OQ}{OP}\right) x \left(\frac{OR}{OQ}\right) = \frac{OR}{OP} = CE \tag{4.12}$$

4.4.2. <u>Revenue Efficiency</u>

Revenue efficiency is measured under output – oriented measures though revenue function. A revenue function aims to maximise the revenue generated by a given set of inputs. The revenue maximizing problem can be written as:

$$r(p,x) = \max_{y} p'y \tag{4.13}$$

St: $$T(y,x) = 0$$

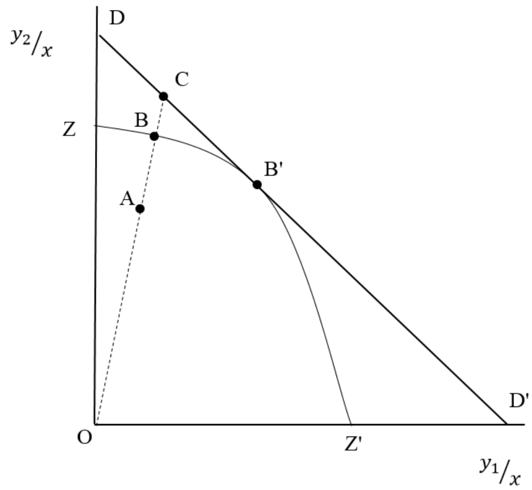
Where $p = (p_1, p_2, \dots, p_M)'$ is a vector of output prices and $T(y,x)$ is the production technology. A revenue function needs to satisfy the following properties (Coelli, T. J. et al. 2005):

1. Non-negativity: Revenue can never be negative
2. Non-decreasing in p: An increase in output prices would not decrease the revenue.
3. Non-decreasing in x: An increase in inputs would produce more output
4. Homogeneity: Multiplying all output prices by an amount $k>0$ will cause a k-fold increase in revenue.
5. Concave in p

Revenue efficiency measurement, according to Farrell, M. J. (1957) is shown in Figure 4.3 . If we assume that a firm produces two outputs, (y_1 and y_2) using a single input *(x),* then the distance AB represents technical inefficiency which is the amount of outputs could be increased using the same number of inputs. So, output oriented technical efficiency ratio is:

$$TE = \frac{OA}{OB} \tag{4.14}$$

Figure 4. 3: Output-orientation Efficiency Measures (technical, allocative and revenue efficiency)



Source: Coelli, T. J. et al. (2005)

The line ZZ' represents production possibility curve which shows the optimal combination of outputs given inputs. A firm that produces at point A is technically inefficient and needs to produce more output given the inputs. If q, $\hat{q}$ and q^* represent, observed output vector of firm associated with point A, the technically efficient production vector associated with point B and revenue efficiency vector associated with point B', respectively, then revenue efficiency of a firm can be defined as:

$$RE = \frac{p'q}{p'q^*} = \frac{OA}{OC} \tag{4.15}$$

We can draw isorevenue line, DD' and define allocative and technical efficiency:

$$AE = \frac{p'\hat{q}}{p'q^*} = \frac{OB}{OC} \tag{4.16}$$

$$TE = \frac{p'q}{p'\hat{q}} = \frac{OA}{OB} \tag{4.17}$$

Furthermore, overall revenue efficiency is defined as:

$$RE = TExAE = \left(\frac{OA}{OB}\right) x \left(\frac{OB}{OC}\right) = \frac{OA}{OC} \tag{4.18}$$

Technical, allocative and revenue efficiency take a value between 0 and 1.

4.5. Estimating efficiency: Parametric Approach

When we talk about the efficiency of the firm, it means if the firm is producing maximum output for given inputs. When talking about economic efficiency, it talks about reduction in costs or an increase in revenue. Therefore, efficiency measures if the resources are being used to get the best value for money.

There are two main ways to estimate efficiency, a parametric approach and a non-parametric approach. The parametric approach is stochastic in nature. It requires specifying a functional form for the underlying technology that might be causing inefficiency. The non-parametric approach is deterministic in nature. It does not require a technology function to determine the efficiency of a firm.

4.5.1. Parametric deterministic Approach

The parametric methods of estimating efficiency require a production function of the underlying technology. The properties of production function have been discussed in section 4.2.

Mathematically different functions can be written in the form of:

$$y = f(x_1, x_2, \dots, x_N) \tag{4.19}$$

Where y is the dependent variable and $x_n (n=1,2,\dots,N)$ is the explanatory variable and f (.) is the mathematical function. So, the first step is to estimate the relationship between the dependent variable and the explanatory variable. Different functional form exist to determine the relationship between dependent and explanatory variables.

Cobb Douglas functional form

In economics, Cobb Douglas functional form is widely used to represent the relations between inputs and outputs. The functional form of the model is given as:

$$P(L, K) = bL^{\alpha}K^{\beta} \tag{4.20}$$

Where P is the total production which is a function of labour, L and capital K. α and β are the output elasticities of labour and capital respectively and b is the total factor productivity. Taking logarithms

$$lnP(L,K) = lnb + \alpha lnL + \beta lnK \tag{4.21}$$

The output elasticities, α and β measure the responsiveness of output to changes in labour or capital used in the production. If $\alpha+\beta=1$, then the production function has constant returns to scale. If $\alpha+\beta>1$, then the production has increasing return to scale and if $\alpha+\beta<1$ then the production has decreasing returns to scale.

The Cobb-Douglas production function can be converted into a cost function where the total costs are a function of output and input prices, which is given as:

$$TC = \alpha_0 \prod_{r=1}^{R} Y_r^{\alpha_r} \prod_{j=1}^{J} W_j^{\beta_j} \tag{4.22}$$

And taking logarithm

$$lnTC = ln\,\alpha_0 + \sum_{r=1}^{R} \alpha_r\, lnY_r + \sum_{j=1}^{J} \beta_j\, lnW_j \tag{4.23}$$

Where TC is the total cost, Y_r is the r^{th} output and W_j is the price of the j^{th} input and α and β are the parameters that need to be estimated. If β is equal to 1 then the cost function is homogeneous of degree one in all inputs. A linear homogeneity implies a proportional increase in input prices would result in the same proportional increase in costs.

Translog functional form

The translog production form is given as

$$lny = \delta + \sum_j \alpha_j lnW_j + \sum_r \eta_r lnY_r + \frac{1}{2}\sum_j \sum_v \kappa_{jv} lnW_j lnW_v + \sum_j \sum_r \gamma_{jr} lnW_j lnY_r + \frac{1}{2}\sum_r \sum_z \tau_{rz} lnY_r lnY_Z \tag{4.24}$$

Where TC is the total cost, Y_r is the r^{th} output and W_j is the price of the j^{th} input. The following restrictions are imposed on the translog cost function to impose linear homogeneity of input prices.

$$\sum_j \alpha_j = 1, \tag{4.25}$$

$$\sum_j \kappa_{jv} = 0 \tag{4.26}$$

$$\sum_j \gamma_{jr} = 0 \tag{4.27}$$

The functional form of cost and production functions can be estimated through linear regression, stochastic frontier and deterministic frontier. The linear regression is estimated though ordinary least squares (Nicholson, F. et al.).

Linear Regression

OLS is a parametric approach which aims to measure efficiency though the estimation of cost or production function in the form of a linear regression. It measures an average cost/production function so some firms will be more efficient while others would be less efficient than the average.

The degree of efficiency is measured through the residuals generated by OLS. The residuals show the difference between the actual and the estimated values. The assumption about the residuals is different in a standard OLS and in the OLS used to measure efficiency. The standard OLS assumes that the residuals are due to statistical noise and the OLS used to measure efficiency assumed that the residuals are due to inefficiencies.

A simple OLS regression takes the form of

$$y_i = \beta_0 + \beta_1 x_i - v_i \tag{4.28}$$

Where y is the output, x is the inputs and v is the error term/ statistical noise/ residual. For OLS regression to give accurate results, certain assumptions need to be made concerning the term

1. Zero mean of v_i

$$E(v_i) = 0$$

2. The error term, v_i is homoscedastic.

$$E(v_i^2) = \sigma^2$$

3. Error terms of firms are uncorrelated

$$E(v_i v_j) = 0 \text{ for all } i \neq j$$

However, the intercept of OLS estimator is biased downwards which restricts us from using OLS to measure technical efficiency. To solve this problem the bias can be corrected for the intercept term by shifting the estimated production function.

Suppose we have an equation to be estimated through OLS

$$lny_i = \beta_0 + \widetilde{x_i}'\tilde{\beta} - v_i \tag{4.29}$$

At first stage OLS regression is run

$$lny_i = \widehat{\beta_0} + x_i'\hat{\tilde{\beta}} + \widehat{e_i} \tag{4.30}$$

Where $\widehat{e_i}$ are the OLS residuals. As the $E(v_i) \neq 0$,the $\widehat{\beta_0}$ obtained from OLS regression is a biased estimate of β_0. However, $\hat{\tilde{\beta}}$ obtained from OLS regression is a consistent estimate of $\tilde{\beta}$. So, the OLS estimation produces consistent slopes but a biased intercept.

We can also obtain OLS regression residual$\widehat{e_i}$:

$$\widehat{e_i} = lny_i - (\widehat{\beta_0} + \tilde{x}_i'\hat{\tilde{\beta}}) \tag{4.31}$$

The value of $\widehat{e_i}$ can be positive or negative. In second stage, the equation for residual is subtracted by $\max\{\hat{e}_i\}$ on both sides so that the OLS intercept is adjusted upwards. The residual equation becomes

$$\hat{e}_i - \max\{\hat{e}_i\} = lny_i - ((\hat{\beta}_0 + \max\{\hat{e}_i\}) + \tilde{x}_i'\hat{\tilde{\beta}}) \leq 0 \tag{4.32}$$

Where $((\hat{\beta}_0 + \max\{\hat{e}_i\}) + \tilde{x}_i'\hat{\tilde{\beta}})$ is the estimated frontier function and estimated inefficiency of the model is given by:

$$\hat{v}_i \equiv -(\hat{e}_i - \max\{\hat{e}_i\}) \geq 0 \tag{4.33}$$

The technical efficiency of each observation is calculated by:

$$\widehat{TE}_i = \exp(-v_i) \tag{4.34}$$

Corrected-OLS assumes that the production frontier is deterministic in nature. So, deviations from the estimated frontier is all assumed due to technical inefficiencies and there is no role for randomness. All the deviations from the frontier are due to the one-sided error component that captures producer inefficiency. Therefore, estimated inefficiency would be highly sensitive to outliers.

4.5.2. Parametric stochastic approach: Stochastic Frontier Analysis

As the name suggests, Stochastic Frontier Analysis (SFA) is stochastic in nature. It is a parametric approach to determine the efficiency of a firm.

The output function of an i^{th} firm is given by:

$$lny_i = x_i'\beta - u_i \tag{4.35}$$

Where y_i is the maximum output achieved by firm i while using inputs x_i. x_i is a vector of non-stochastic logarithm inputs and β is a vector of unknown parameter and u_i is a non-negative random variable associated with technical efficiency. This production frontier is deterministic in nature. This creates a problem, as it does not take into account the measurement error and statistical noise. The statistical noise arose due to the omissions of relevant variables from vector of x_i. It can lead to deviations in the frontier that are assumed to be due to technical inefficiency.

To solve this issue, another variable needs to be introduced which can represent statistical noise. Aigner, D. et al. (1977) and Meeusen, W. and van Den Broeck, J. (1977) independently proposed a SFA model in which they presented another variable. The functional model took the form:

$$lny_i = x_i'\beta + v_i - u_i \tag{4.36}$$

They added a variable v_i which accounted for the statistical noise. v_i is assumed to be iid $N(0, \sigma_v^2)$. To explain it further, (Coelli, T. J. et al. 2005) took an example of a simple Cobb-Douglas stochastic frontier model with single input and output.

$$lny_i = \beta_0 + \beta_1 lnx_i + v_i - u_i \tag{4.37}$$

Or:
$$y_i = \exp\,(\beta_0 + \beta_1 lnx_i + v_i - u_i) \tag{4.38}$$

Or:
$$y_i = \exp(\beta_0 + \beta_1 lnx_i) \times \exp(v_i) \times \exp\,(-u_i) \tag{4.39}$$

Where $\exp(\beta_0 + \beta_1 lnx_i)$ is the deterministic component, $\exp(v_i)$ is the noise and $\exp(-u_i)$is the inefficiency.

Figure 4.4 shows the frontier of two firms, A and B. Firms A uses input x_A to produce output y_A while firm B uses input x_B to produce output y_B. This gives us the model:

$$y_A = \exp(\beta_0 + \beta_1 lnx_A + v_A - u_A) \tag{4.40}$$

And

$$y_B = \exp(\beta_0 + \beta_1 lnx_B + v_B - u_B) \tag{4.41}$$

If there is no inefficiency i.e. $u_A = 0$ and $u_B = 0$, the frontier output would be

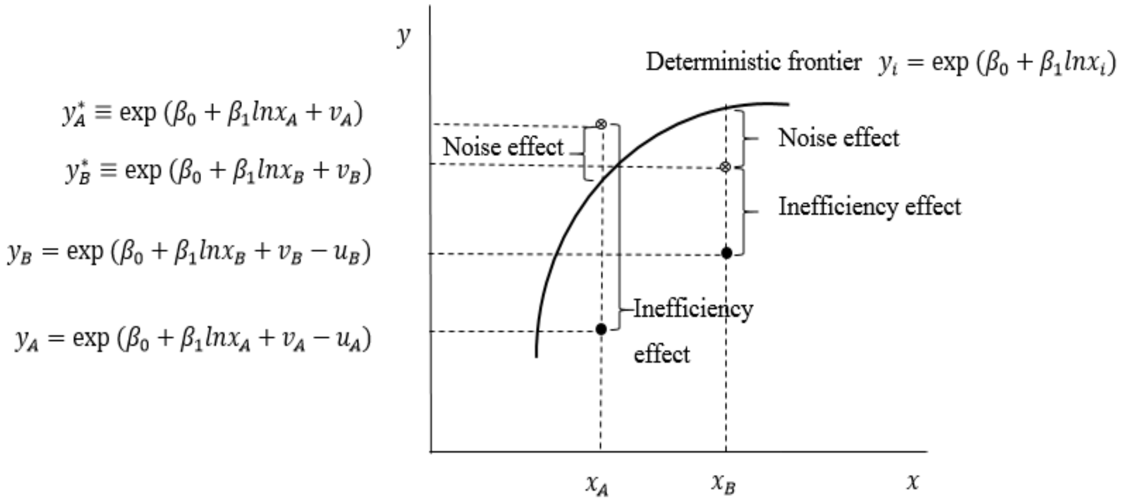
$$y_A^* \equiv \exp(\beta_0 + \beta_1 lnx_A + v_A) \tag{4.42}$$

And

$$y_B^* \equiv \exp(\beta_0 + \beta_1 lnx_B + v_B) \tag{4.43}$$

Where the * values are the frontier values.

Figure 4. 4: Stochastic Frontier



Source: Coelli et al. (2005)

The points marked • are the observed values and points marked ⊗ are the frontier values. The distance between the observed values and frontier values is the inefficiency effect. The noise effect is the distance between the frontier values and the deterministic frontier. The frontier output of Firm A lies above the deterministic frontier as the noise effect is positive ($v_A > 0$). The observed value of Firm A lies below the frontier as the sum of noise and inefficiency effect is negative ($v_A - u_A < 0$). Firm B's observed value and frontier value lies below the deterministic frontier. The noise effect is negative($v_B < 0$).

SFA measures the inefficiency effects. These effects can be calculated by measuring the technical efficiency of firms. The technical efficiency ratio is the ratio of observed output to the corresponding stochastic frontier output.

$$TE_i = \frac{y_i}{\exp(x_i'\beta + v_i)} = \frac{\exp(x_i'\beta + v_i - u_i)}{\exp(x_i'\beta + v_i)} = \exp(-u_i) \tag{4.44}$$

So the $\exp(-u_i)$ gives us the ratio of actual output to the maximum possible output (Kumbhakar, S. C. et al. 2015). The technical efficiency score for i^{th} firm takes the value between 0 and 1 as $u_i \geq 0$. It compares the actual output of the i^{th} firm with the output that can be achieved if the firm was fully efficient while using same input vectors

4.6. Estimating Efficiency- Non-parametric approach (DEA)

In the previous section of this chapter we described methodology to estimate efficiency using functional form. However, when the functional form is not known, then a non-parametric approach of Data Envelopment Analysis (DEA) can be used.

The methodology of DEA was first proposed by Charnes, A. et al. (1978) which was based on the paper on efficiency by Farrell, M. J. (1957). Farrell, M. J. (1957) laid the foundations of the new approach on efficiency and productivity in which he discussed measurement of efficiency of a firm with a single input creating a single output. His efficiency measures were based on the radial contraction and expansion from the inefficient unit to the frontier. The frontier was created through a system of linear equations rather than an underlying technology. Farrell, M. J. (1957) measurement of efficiency became the basis of the paper by Charnes, A. et al. (1978) who introduced linear programming model with multiple inputs and multiple outputs. The linear programming model brought forward by Charnes, A. et al. (1978) was a constant returns to scale (CRS) model and is know in literature as CCR model, named after the authors. The CCR model was extended by Banker, R. D. et al. (1984) by adding a convexity constraint to convert a CRS model to a variable returns to scale model (VRS). This modification to the CCR model became known as BCC model, named after its authors.

The DEA is a non-parametric method which uses inputs and outputs to construct a best linear frontier for given data. This frontier is constructed using the solutions of various linear programming problems. It allows us to measure the degree of technical inefficiency by calculating the distance between the observed data points and the best linear frontier.

The DEA evaluates the performance of a set of peers known as Decision Making Units (DMUs). These DMUs are responsible for converting multiple inputs into multiple outputs. DEA aims to evaluate the performance of these DMUs. In managerial application, the DMUs can be banks, supermarkets, stores, hospitals or schools. In engineering, the DMUs can take the form of aeroplanes (Cooper, W. W. et al. 2000). For our study, we take the individual farms as DMUS and aim to evaluate their performance.

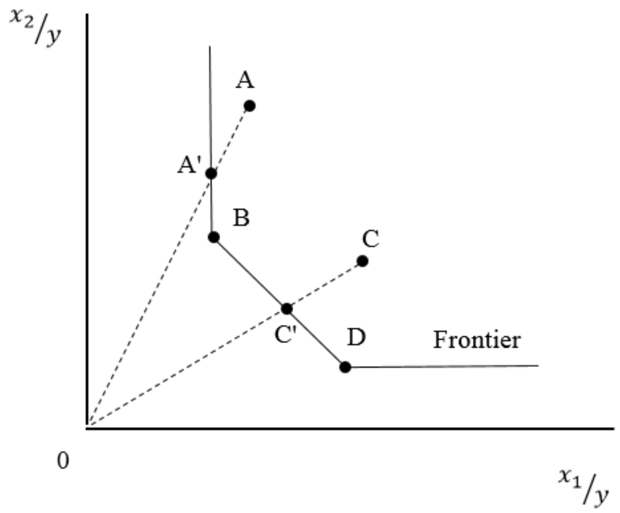
DEA can be either input oriented or output oriented. If the DEA is input oriented then its aim is to maximise the decrease in the proportion of inputs used given an output. However, if the DEA is output oriented, it constructs a frontier such that it maximises the proportion of output given the input.

4.6.1. Input Oriented DEA

The theory behind input-oriented DEA was introduced by Farrell, M. J. (1957) and formally presented by Charnes, A. et al. (1978) in which the inputs were minimised to produce the level of output as before. An input-oriented DEA is shown in Figure 4.5.

We take a simple example with four firms, A, B, C and D. These firms are the DMUs who use two inputs (x_1, x_2), to produce one output (y). We can plot the input/output ratio for each input to create a frontier. The DMUs which are on the frontier are technically efficient. The area on the right of the frontier is known as the production possibility set (PPS). This PPS is the set of feasible activities.

Figure 4. 5: Input-Oriented DEA



Source: Coelli, T. J. et al. (2005)

Firm B and firm D lie on the frontier and so they are technically efficient. Firms A and C lie above the frontier and so are technically inefficient. For these firms to become efficient, they would have to reduce the use of their inputs to produce the same amount of output. The efficiency score θ can be calculated by taking the ratio $0A'/0A$. $0A'$ is the distance from the origin to the point A' that crosses the frontier and $0A$ is the distance from the origin to point A. The efficiency score would be between 0 and 1.

Let's suppose that the efficiency of firm A is 0.8. It would mean that firm A is using 80% of its inputs correctly and can potentially reduce the use of its inputs by 20% to become efficient. The reduction in usage of both inputs is going to be proportional.

Another thing that we can gather from Figure 4 are the peers of the inefficient firms. The term peer literally means friends. In this context, peer refers to the firms which are similar and close to each other.

The firm A is inefficient and for it to be efficient it needs to move to point A' which lies on the frontier. This projected point, A' , joins to point B. So, the peer of firm A is firm B. Similarly, firm C is inefficient and to become efficient it needs to reduce the use of its inputs so that it can lie on point C'. This project point C' lies on the line joining points B and D. So, firm's B and D are peers to firm C and point C' is a linear combination of point B and D.

Constant Return to Scale

An input oriented, constant returns to scale (CRS) DEA model was proposed by Charnes, A. et al. (1978) and is known as CCR model. The assumption of having constant returns is appropriate when the firms are operating at an optimal scale. Constructing a model where there are N number of inputs and M number of outputs for each of I firms. For an i^{th} firm, inputs and outputs are represented by column vectors x_i and y_i, respectively. X represents input matrix *NxI* and output matrix Y is *MxI* which represents the data for all I firms.

Model 1: CCR - I

$$\left.\begin{aligned} & min_{\theta,\lambda} \quad \theta, \\ \text{St:} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0 \\ & \lambda \geq 0, \end{aligned}\right\} \quad (4.45)$$

Where θ is a scalar that is the efficiency score for the i^{th} firm and λ is a $Ix1$ vector of constants. The efficiency score, $\theta,$ can take value between 0 and 1. A value of 1 indicates that the DMU is on the frontier and is technically efficient.

Variable Return to Scale

Not all firms can operate at an optimal scale. Some firms are generally not operating on an optimal scale due to financial constraints, imperfect competition, and regulations. So, if technical efficiency is calculated for these firms using CRS, it would result in wrong estimates. So Banker, R. D. et al. (1984) suggested adjusting the CRS DEA to take into account the variations. The CRS linear programming problem can be easily modified for the variable return to scale (VRS) by adding the convexity constraint, $I1'\lambda = 1$. This constraint would ensure that the firms are benchmarked against the firms that are of similar size (Coelli, T. J. et al. 2005). So, we would have the following model which is known as BCC model:

Model 2: BCC - I

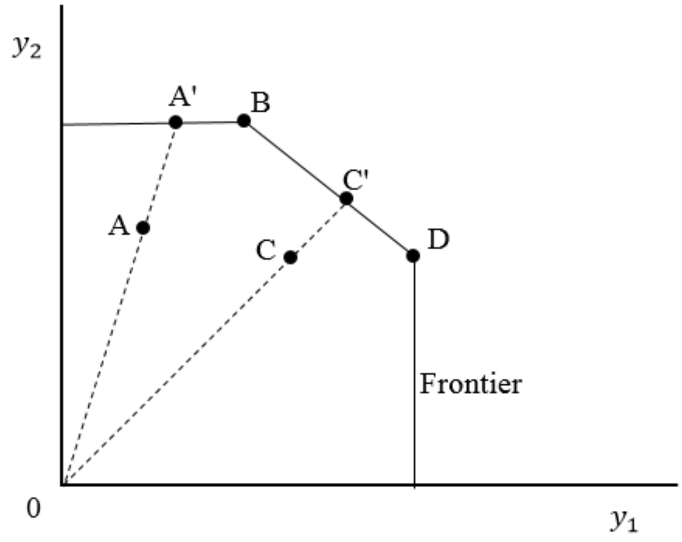
$$\left.\begin{array}{ll} & min_{\theta,\lambda} \quad \theta, \\ \text{St:} & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0 \\ & I1'\lambda = 1 \\ & \lambda \geq 0, \end{array}\right\} \quad (4.46)$$

Where *I1* is an *IX1* vector of one, and *I* are the total number of firms. This convexity constraint is not implemented in CRS. So, in CRS, firms would be benchmarked against the firms that are larger or smaller than it. The efficiency score, θ takes the value between 0 and 1. If the score is 1 then the firm is technically efficient and lies on the frontier, as mentioned before in CRS DEA.

4.6.2. Output Oriented DEA

The output-oriented DEA measures technical efficiency as a proportional increase in output while keeping inputs constant. Figure 4.6 presents the production possibility for the two outputs. The firms operating inside the PPS are inefficient and are producing less output given the inputs. We have an example of four firms *A*, *B*, *C* and *D*. Firm *B* and *D* lie on the frontier so they are the efficient firms. The firm's *B* and *D* lie on the frontier so they are technically efficient however firms *A* and *C* lie inside the PPS and so are inefficient. The firms *A* and *C* can increase the production of their outputs by using the same level of inputs. The efficiency is calculated by taking the ratio *0A'/0A* where A' is the point projected onto the frontier.

Figure 4. 6: Output-Oriented DEA



Source: Coelli, T. J. et al. (2005)

Constant Return to Scale

According to Coelli, T. and Rao, D. S. P. (2005), both the input and output-oriented DEA models provide the same results for technical efficiency index if the returns to scale are constant. However, if the returns to scale are variable then the technical efficiency index may vary as the frontier would be different. A simplified model of output-oriented DEA is given with CRS. Using the annotation given in the previous section we have a model:

Model 3: CCR - O

$$\left.\begin{aligned} & max_{\phi,\lambda} \quad \phi \\ \text{St:} \quad & -\phi y_i + Y\lambda \geq 0 \\ & x_i - X\lambda \geq 0 \\ & \lambda \geq 0 \end{aligned}\right\} \quad (4.47)$$

Where $1 \leq \phi \leq \infty$ and ϕ-1 is the proportional increase in outputs that could be achieved by the i^{th} firm with the input quantities unchanged. The output oriented technical efficiency score is provided by $1/_{\phi}$, which takes the value between 0 and 1 (Coelli, T. J. et al. 2005).

Variable Return to Scale

The output oriented VRS model was proposed by Banker, R. D. et al. (1984) which takes into account the convexity condition mentioned in the previous chapter. The output-oriented VRS model is given by:

Model 4: BCC- O

$$\left.\begin{aligned} &max_{\phi,\lambda} \quad \phi, \\ \text{St:} \quad &-\phi y_i + Y\lambda \geq 0 \\ &x_i - X\lambda \geq 0 \\ &I1'\lambda = 1 \\ &\lambda \geq 0, \end{aligned}\right\} \qquad (4.48)$$

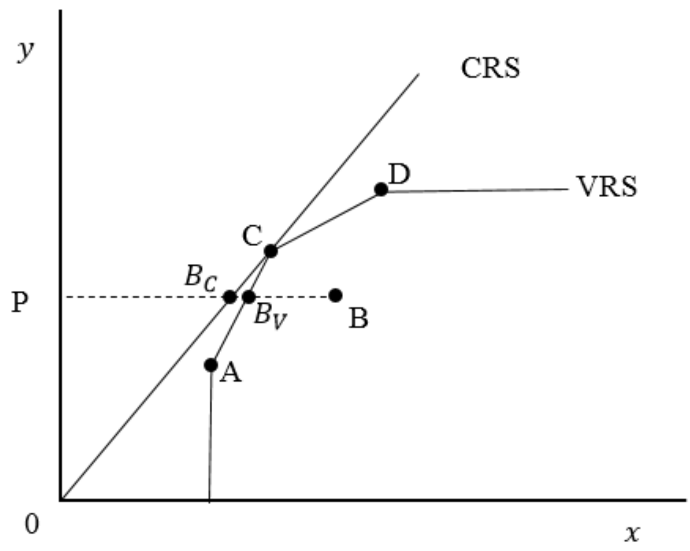
Where a convexity constraint, $I1'\lambda = 1$, is added to the CRS output-oriented model. The technical efficiency score is given by $1/\phi$ bounded between 0 and 1. The convexity constraint allows the firm to be benchmarked against the firm similar to its size. If the firm is smaller, the sum of λ-weights would be greater than 1 and if the firm in larger, then that λ-weights are smaller than 1 (Coelli, T. J. et al. 2005).

4.6.3. Scale efficiency and returns to scale

The CRS assumes that the firms are operating at an optimal level. A firm is operating under CRS if the proportional increase in its inputs leads to a proportional increase in its outputs. However, for the firms that operate under VRS, the increase in its inputs would lead to a non-proportional increase in its outputs.

Figure 4.7 shows the frontier under CRS and VRS. There are four firms, *A, B, C* and *D*. Firms A, *C* and *D* lie on the VRS frontier so they are technically efficient. However, only firm *C* lies on the CRS frontier so only that firm is efficient. Firm *B* is inefficient under bother CRS and VRS.

Figure 4. 7: Scale Efficiency



Source: Coelli, T. J. et al. (2005)

The technical efficiency of firm B under VRS is calculated as:

$$TE_B^{VRS} = \frac{PB_V}{PB} \tag{4.49}$$

And the technical efficiency of firm B under CRS would be:

$$TE_B^{CRS} = \frac{PB_C}{PB} \tag{4.50}$$

The difference in the ratio of efficiency between CRS and VRS is known as scale efficiency that can be written as:

$$SE_B = \frac{PB_C}{PB_V} = \frac{TE_B^{CRS} \times PB}{TE_B^{VRS} \times PB} = \frac{TE_B^{CRS}}{TE_B^{VRS}} \tag{4.51}$$

Therefore, the technical efficiency under CRS can be decomposed into technical efficiency under VRS and scale efficiency.

$$TE_B^{CRS} = TE_B^{VRS} \times SE_B \tag{4.52}$$

The TE_B^{VRS} can be thought as 'pure' technical efficiency. This would allow us to decompose the TE_B^{CRS} into pure technical efficiency and scale efficiency. So we would know if the inefficiency is due to inefficient operations or is it due to disadvantageous conditions set by the scale, or both (Cooper, W. W. et al. 2000).

The scale efficiency takes a value between 0 and 1. If the scale efficiency is 1, it indicates that the DMU is scale efficient and $TE^{CRS} = TE^{VRS}$. If the scale efficiency score is less than 1 then it means that the DMU can increase its efficiency by changing the size of its operations (Coelli, T. J. et al. 2005).

Although scale efficiency allows us to know if the firm is operating on a productive scale or not, but it doesn't indicate if a firm is operating with increasing or decreasing returns to scale (Coelli, T. J. et al. 2005). This problem is solved by adding restrictions to our previous models. In BCC model where we had VRS, the convexity constraint, $I1'\lambda = 1$ was added to the model to allow flexibility. The constraint is changed to, $I1'\lambda \leq 1$ to ensure that i^{th}firm is not benchmarked against the firms that are larger than it is. Therefore, the model changed to:

Model 5: Non-increasing return to scale

$$\left.\begin{aligned} &min_{\theta,\lambda} \qquad \theta, \\ \text{St:} \quad &-y_i + Y\lambda \geq 0 \\ &\theta x_i - X\lambda \geq 0 \\ &I1'\lambda \leq 1 \\ &\lambda \geq 0 \end{aligned}\right\} \tag{4.53}$$

The nature of the scale inefficiencies can be determined by comparing the technical efficiency score obtained by model 1 and model 5. If the scores are equal then there is decreasing return to scale and if the scores are unequal then there is increasing returns to scale.

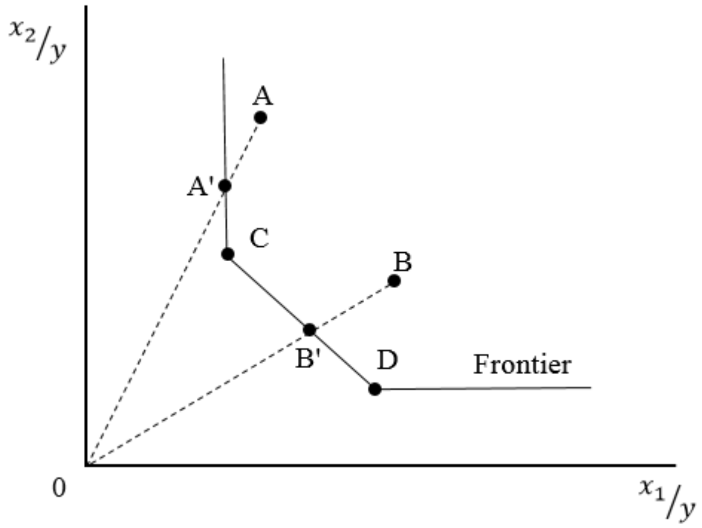
4.6.4. Additive models

The models discussed in the previous section require us to distinguish between input and output orientation. Charnes, A. et al. (1985) introduce additive models that are a combination of input and output-oriented models.

Slack-based models

The linear form of the non-parametric frontier in DEA can cause difficulties in measurement of efficiency. The problems arise due to the section of the frontier that runs parallel to the axis. This is illustrated in Figure 4.8 where the input to output ratio for four firms (*A*, *B, C* and *D*) is plotted. Firms *C* and *D* are efficient firms as they lie on the frontier and firms *A* and *B* are inefficient. The technical inefficiency of firms *A* and *B* can be calculated using the approach by Farrell, M. J. (1957).

Figure 4. 8: Slack-Based DEA model



Source: Coelli, T. J. et al. (2005)

The efficiency score θ can be calculated by taking the ratio *0A'/0A* and *0B'/0B* for firm *A* and *B*, respectively. However, the question raised is that is point A' an efficient point since the same output can be produced by just decreasing the amount of input x_2 used. This is known as input slacks. In the models with multiple inputs and multiple outputs, then output slacks can occur. Let us assume that firm's *A*'s technical efficiency score, $\theta = 0.5$. This mean that firm *A* would have to reduce the use of inputs by 50% to produce same output and reach point A'. Since point A' lies on the portion of the frontier that is parallel to the axis, a further reduction in input x_2 can be done to achieve the same output. This would result in firm *A* moving from point A' to point *C* as firm *C* is firm A's peer (Coelli, T. J. et al. 2005).

Suppose that there are *I* DMUs, using N inputs to produce M outputs. They can be denoted as $x_n(n = 1, \ldots, N)$ and $y_m(m = 1, \ldots, M)$ which are positive. The slack based measure (SBM) efficiency score of i^{th}DMU, denoted as DMU_0, is given by the following program (Tone, K. 2001):

$$min_{\lambda,\theta} \qquad \rho *= \frac{1-(\frac{1}{N})\sum_{n=1}^{N} s_{n0}^{-}/x_{n0}}{1-(\frac{1}{M})\sum_{m=1}^{M} s_{m0}^{+}/y_{m0}}$$

St:
$$x_{n0} = \sum_{i=1}^{I} x_{ni}\lambda_i + s_{n0}^{-} \qquad (4.54)$$

$$y_{m0} = \sum_{i=1}^{I} y_{mi}\lambda_i - s_{m0}^{+}$$

$$\lambda \geq 0, \quad s^{-} \geq 0, \quad s^{+} \geq 0,$$

Model 6: Slack Based Models

The vectors s^{-} and s^{+} indicate the input and output slack, respectively. If the DMU_0 is effecienct then all its slacks are going to be equal to zero. It would mean that there is no need for reduction in inputs or increase in outputs. If the slack value is non- zero, it would indicate that the DMU_0 is inefficient and would point towards which input or output is contributing towards its inefficiency. The $DMU_0(x_0, y_0)$ can become efficient by removing the input excess and by augmenting the output shortfall (Tone, 2001).

$$x_0 \leftarrow x_0 - s^{-*}$$

$$y_0 \leftarrow y_0 + s^{+*}$$

Dealing with zero input/output data

So far, all the data that we deal with assumes that the input and output vector have all non-zero values. The constraint placed in all the above-discussed models is $X > 0$ and $Y > 0$. However, we need to expand the models to allow for zero values so that the data can mimic real world.

Tone, K. (2001) proposed to modify constraints in Slack Based Models to allow for zero values. Assuming that one of the inputs (x_0) has zero values, then $x_{10} = 0$ and so the model becomes:

$$\sum_{i=1}^{I} x_{1i}\lambda_i + s_1^{-} = x_{10} = 0 \qquad (4.55)$$

For a feasible solution $s_1^{-} = 0$. Therefore, we can remove s_1^{-} from the set of variables that need to be determined by the model. The term s_1^{-}/x_{10} should be removed from the objective function and *N* should be reduced by 1 i.e.$N \rightarrow N - 1$. This would give us the SBM for an input with zero values.

Suppose that there is zero in output data, and so $y_{10} = 0$. The output constraint can be modified to become:

$$\sum_{i=1}^{I} y_{1i}\lambda_i - s_1^+ = y_{10} = 0 \tag{4.56}$$

We need to consider 2 cases:

<u>*Case 1:*</u> When the DMU in question possesses no function of producing the output.

In this case, we can remove the term s_1^+/y_{10} as the would be no slacks and *M* should be reduced by 1 ($M \rightarrow M - 1$).

<u>*Case 2:*</u> When the DMU possess ability to produce the output but does not utilise it

In this case, the output y_{10} can be replaced by a smaller number or by:

$$y_{10} \leftarrow \frac{1}{10}\min\{y_{1i}|y_{1i} > 0\} \tag{4.57}$$

In this case, we cannot remove the term s_1^+/y_{10} from the objective function as it plays the role on penalty.

Non- Discretionary Variables

In the above-discussed models of DEA, we assume that the input and output quantities are fixed in the short and the long run by the manager. However, in reality, we cannot fix some variables in the short term. Taking the example of dairy farms, variables such as land and buildings cannot be controlled by the farmer in the short run. This section deals with the variables that are not under the control of a manager.

The DEA models need to modify in such a way that they can reduce the input usage of some variables while keeping others fixed. Non- discretionary variables are those, which cannot be changed, in the short run. We seek the radial reduction in the input usage of discretionary variables. Modifying the system of equations 4.46 we can divide the input variables into discretionary (X^D) and non- discretionary variables (X^{ND}).

Model 6: Non-discretionary variables DEA

$$
\left.\begin{array}{ll}
 & \min_{\theta,\lambda} \quad \theta, \\
\text{St:} & -y_i + Y\lambda \geq 0, \\
 & \theta x_i^D - X^D\lambda \geq 0, \\
 & x_i^{ND} - X^{ND}\lambda \geq 0, \\
 & I1'\lambda = 1 \\
 & \lambda \geq 0
\end{array}\right\} \quad (4.58)
$$

The parameter of θ is only associated with the discretionary input as we only seek to reduce these inputs radially.

4.7. *Why DEA?*

The parametric techniques most frequently used is the Stochastic Frontier Analysis (SFA). The parametric techniques use the best available technology to estimate a production function. This technique allows the researcher to construct confidence intervals and perform hypotheses testing with a robust framework (Hjalmarsson, L. et al. 1996). Furthermore, SFA can distinguish the effect of statistical noise from inefficiency (Reinhard, S. et al. 2000), something that DEA cannot do.

However, the problem with this method is that the researcher has set a prior assumption on the relation of the functional form for the technology frontier which can bias the results. Due to being parametric in nature, misspecification of the functional form can lead to errors in estimation of inefficiency (Reinhard, S. et al. 2000).

Arnade, C. A. (1994) pointed out that these traditional measures which use an aggregate production function as the basis for measuring productivity are faulty aggregate assumptions. These assumptions lead to the limitation of the functional form and produce different estimates of productivity. These approaches are common because they are simple to calculate, do not require econometric estimations and the data required are minimal (Kumar, P. et al. 2008).

The most important aspect of DEA is that it does not require any assumptions to about the functional form, so there is no restriction. So DEA does not need an assumption about the technology to expect for the convexity constraint (Hjalmarsson, L. et al. 1996). DEA is a mathematical model which can be applied to the data to provide us with the empirical estimates. Rather than fitting regression to the data, DEA allows the frontier to rest on top of the observations. Due to this DEA will enable us to uncover hidden relationships (Seiford, L. M. and Thrall, R. M. 1990).

A variety of studies have compared DEA results with SFA to determine which method provides accurate results. Hjalmarsson, L. et al. (1996) analysed several models based on DEA and SFA to examine differences between them. They took the example of the cement industry and tested for variable and constant returns to scale models. They found that the efficiency decreased in both the DEA and SFA models over the years. They also found a strong correlation between the mean efficiency scores between VRS DEA and SFA model with controlled variables.

Reinhard, S. et al. (2000) also compared the efficiency results obtained from DEA and SFA. They used the example of Dutch dairy farms and incorporated environmental variables to determine which methods could accurately calculate environmental efficiency. They found that the environmental efficiency scores obtained from DEA were lower than the efficiency scores obtained from SFA. The technical efficiency under SFA was approximately 10% higher than the efficiency under DEA as SFA's results considered statistical noise. However, both the techniques provided similar rankings of farms based on various efficiency criteria.

Bravo-Ureta, B. E. et al. (2007) conducted a meta-regression analysis on the technical efficiency in farming. They evaluated 167 papers from 1979 to 2005 which estimated efficiency either using deterministic or stochastic models. They found that the average efficiency estimates were higher for non-parametric model compared to parametric models and lower for a deterministic model than the stochastic ones. Using OLS and Tobit for meta-regression, they found that the non-parametric deterministic (DEA) models yielded higher score than the parametric stochastic (SFA) models.

Odeck, J. and Bråthen, S. (2012) conducted a meta-analysis of DEA and SFA studies on seaports using random and fixed effects regression models. They considered 40 studies which comprised of 29 DEA studies and 11 SFA studies. The DEA studies began from 1993 whereas the SFA studies started in 1983 implying popularity of DEA in recent years. The studies based on DEA generated higher average efficiency than the SFA studies. The higher average technical efficiency scores in DEA models were due to DEA generating more DMUS whose technical efficiency was equal to 1.

Fall, F. et al. (2018) conducted a meta-regression analysis on the studies on efficiency of microfinance institutions. Similar to Bravo-Ureta, B. E. et al. (2007) and Odeck, J. and Bråthen, S. (2012), they found that the mean technical efficiency was higher for DEA models than SFA models.

None of the studies stated that one method of estimating efficiency was better than the other methods. However, they all emphasised that the choice of the efficiency method should be made by keeping in mind the trade-offs between the approaches.

A variety of studies have used DEA for the measurement of the efficiency of dairy farms. Wettemann, P. J. C. and Latacz-Lohmann, U. (2017) estimated the cost and environmental efficiency of German dairy farms using DEA. Rather than using the environmental variable as an input or as an undesirable output, they followed and derived GHG shadow prices for inputs.

A study was conducted by Kelly, E. et al. (2012) on the technical efficiency of Irish dairy farms. Inputs used in their DEA model were the land area in hectares, average number of dairy cows, labour units in hours, kilograms of purchased concentrates and fertilisers and other costs. The output variable taken was milk solids per farm in kilograms. The average technical efficiency score for 190 dairy farms using CRS was 78.5% and under VRS was 83.3%. The efficiency score under VRS was higher than the average efficiency score under CRS. Approximately 16% and 23% of the farms in their sample were CRS and VRS efficient, respectively. They then compared the characteristics of technically efficient and inefficient farms. They found that technically efficient farms produced 33% more milk solids than inefficient producers. Milk solids per cow and hectare were also higher for efficient producers. For the other variables, such as land, labour, and number of cows, there were no statistically significant differences among efficient and inefficient producers.

They further compared producers having an efficiency score above 0.9 but below 1 with producers having an efficiency score below 0.9. This comparison was carried out to test the robustness of the results. They wanted to check if the factors that were statistically significantly different between efficient and inefficient farms would remain significant with lower levels of technical efficiency. The results showed that the variables that were significant before remained significant for lower efficiency scored farms.

Silva, E. et al. (2013) measured the technical efficiency of 122 dairy farms in the Azores, Portugal using DEA. They selected agricultural area, number of cows and variable and fixed costs as inputs and milk production and subsidies as outputs. Using CRS, they found that 7.4% of the farms were technically efficient and the average efficiency score was 66.4%. The average technical efficiency score from VRS was 78.2% showing that efficiency scores are higher under VRS compared to CRS. There was no relation between the technical efficiency and the level of milk production. However, the cost of milk production per hectare was lower for technically efficient farms but, no relationship was found between milk production per hectare and technically efficient farms.

Hambrusch, J. et al. (2006) measured the technical and scale efficiency of 222 dairy farms in Austria. They used labour hours, the number of cows, land in hectares, other expenses, the value of machinery and the cost of animal husbandry as inputs and the quantity of milk produced and other revenue as outputs. Using input-oriented DEA, they found that the average pure technical efficiency (which is VRS technical efficiency) score was 84% and average scale efficiency was 94% implying that 6% of the total inefficiency could be removed by farms adopting efficient farm size. The technically efficient farms were found in all size categories indicating that other factors such as management practices play an important role in determining the efficiency of a farm.

Spicka, J. and Smutka, L. (2014) evaluated the productive efficiency of specialised dairy farms in EU regions. For efficiency calculation, they took UAA in hectares, labour hours, material cost energy costs, capital costs and contract work as inputs and output of the farm in Euros as output. Using VRS-DEA, they found that 45 regions were technically efficient while 63 regions were inefficient. The efficient regions had larger farms in terms of area and used more labour hours per farm. Efficient dairy farms also had a larger herd size so they had a higher stocking intensity. However, no statistically significant differences were found between technically efficient and inefficient farms with regards to milk yield and labour hours per cow.

For the purpose of this thesis, we would be employing DEA for efficiency measurement. DEA's property of unit invariance would allow us independence of units in which inputs and outputs are measured. One of the biggest motivation of using DEA is that it does not require a production function and hence we can avoid estimation errors due to misspecification of the functional form.

4.8. Conclusion

This chapter has introduced the theory of efficiency and productivity and has outlined several approaches to estimate them. The methods to measure efficiency were categorised into parametric and non-parametric approaches. The parametric approach of evaluating efficiency included SFA, OLS and COLS. The parametric approach required an estimation of a production frontier. However, the alternative approach of non-parametric efficiency estimation did not need a functional form. This chapter provided a comprehensive review on the estimation of efficiency through DEA models. A variety of DEA models like input- oriented, output-oriented and additive models were discussed.

Lastly, we reviewed a few studies that compared the efficiency estimates obtained from DEA and SFA and found that the choice of methodology largely depends on the discretion of the researcher.

The detailed methodology of cluster analysis, β and σ-convergence and Tobit regression is provided in their own chapters. The following chapter would outline the data used in this study to examine the efficiency of dairy farms in Wales and England.

5. THE DATA

5.1. Introduction

The previous chapter outlined the theory of efficiency and explained the measurement of efficiency. We determined that the efficiency of dairy farms in this thesis is going to be measured through the application of the Data Envelopment Analysis (DEA). The choice of data for the measurement of efficiency is very important. This section outlines the main data used for efficiency analysis. Furthermore, this chapter aims to calculate the greenhouse gas (GHG) emissions from the dairy farms using the guidelines given by Intergovernmental Panel on Climate Change (IPCC).

The data for this study has been collected from the Farms Business Survey for 4505 farms in Wales and England over a 10 year period (2006-2015). It a small sample compared to the total number of farms in Wales and England and so does not represent the national position. Using the data obtained from the FBS, we find that the size of the farms in terms of the area has remained relatively unchanged but the herd size in both England and Welsh farms is increasing. With the increase in the number of cows per farm, the inputs like labour hour and the cost of feed have risen. However, we found that the greenhouse gas (GHG) emissions have declined over the years.

The structure of this chapter is as follows: section 2 discusses how data was acquired from the FBS. In section 3 we look at area allocated for agriculture in Wales and England. In section 4, the cow numbers and milk production is discussed. In section 5 we explore the contribution of labour to dairy farming. In section 6 we evaluate the costs of feed on the farm for the animals. The estimation of GHG is presented in section 7. Lastly, section 8 concludes the chapter.

5.2. Farm Business Survey (FBS)

As we are focusing more on dairy farms in Wales and England, most data used has been taken from the Farm Business Survey (FBS). The FBS is an annual survey that provides information on the financial, physical and economic performance of farms. The sample of farms cover all the regions in England and Wales and covers all farm types. The farms are divided into 10 types: Cereals; General cropping; Horticulture; Specialist pigs; Specialist poultry; Dairy; LFA grazing Livestock; Lowland grazing livestock; Mixed and Others.

The classification of farm business by type is simple when the farm only has one type of activity. When a farm engages in more than one type of agricultural activity, then the FBS classifies the farms according to the contributions of different crops or livestock type. Standard Outputs (SOs) are calculated per hectare of crops or head of livestock. The SO represents the level of output that is expected on a farm under normal conditions. A farm is allocated to a particular category of the farm types mentioned above when the output from crop or livestock type is more than two-thirds of its total output (DEFRA 2014).

The FBS is a comprehensive database published by the UK government. However, there are certain limitations to it. Firstly, the sample structure of the FBS is routinely re-designed and new questions are added every other year which makes it difficult to compare the past values. Another problem is of sampling error[13]. The FBS has been designed in such a way, that it takes minimum effort to be filled in. However, some farmers are unwilling to participate due to the sensitive nature of the data. Therefore, the survey only covers a small sample of the population which means that there is a degree of sampling error. The FBS included the data from 1,750 farms in England and 550 Welsh farms. Approximately 20% of the farms covered by the FBS are specialised dairy farms.

The FBS collects data from individual farms so the data from these farms is considered confidential and is not available freely. To get access to the data, a special request was made to the UK Data Archives. The survey itself is in the form of an 82-page booklet. The number of pages varies over the years as new information is added every year. The FBS booklet has 17 sections and every section aims to record farms' different characteristics and information. In every section, the information is recorded in a table format. Each farm fills its own individual booklet. The data is processed by principal investigators, Department for Environment, Food and Rural Affairs (DEFRA), National Assembly for Wales until the year 2010 and by Duchy College, Rural Business School from 2011 onwards.

The data provided to users for research and analysis comes in the form of a MS Access file where each row of data relates to an entry for a given farm. The farms are representing as a number so that the anonymity of the farms is maintained. There are eight columns in MS

[13] The sampling error is the difference between the estimates derived from the sample and the true values that would be estimated if the whole population was considered

Access file which record information. The first column is the Farm Number which is a unique number given to identify a specific farm.

The second column refers to the section in the FBS booklet. The third column represents rows and the fourth column represents the column in the booklet in a specific section. The fifth column records the Crop Type (only applicable to section C in the booklet). The sixth column records missing data codes for when data is not or cannot be provided. The seventh column is used for processing purposes and not for our use. the last column is of Field Value where the value referenced by section row and column is entered.

For example, the date of birth of a specific farmer, which is recorded in the FBS booklet section B, row 1 and column 2 of the FBS booklet, is presented in MS Access file in the form below (DEFRA 2018d).

Farm Number	Section	Row	Column	Crop Type	MDC	Load number	Field Value
e.g 9999	B	1	2	0	0	12	1952

Thus, the farmer in the farm number 9999 was born in 1952. So, to extract specific information required in this study, it was important to know the section, row and column of the variables required.

For this study, only farms with more than 20 dairy animals were considered. So, the variable was identified in the FBS and specific farms that met the criteria were extracted from the MS Access files. This was done for every individual year as the farms in the data sample varied over the years and so did the number of dairy cows on a farm. Once those farms were identified, the rest of their information was extracted and recorded in a MS Excel file to create a database.

The FBS collects information on a variety of aspects of farm business such as labour use, crop and livestock population, financial information and off-farm activities. Thus, the FBS is a unique source of time series data (McNally, S. 2001). The main use of FBS is to collect data for the Farm Accountancy Data Network (FADN) (DEFRA 2018d). The FADN is an instrument used to provide business information on European agricultural holdings and to evaluate the impacts of Common Agricultural Policy (CAP). The FADN data is collected by various agencies in the EU member states. In the UK, the Department for Environment, Food and Rural Affairs (DEFRA), for Wales and England, collects the data for FADN through the FBS (DEFRA 2018d; Lynch, J. et al. 2018).

The data from FBS has been used in various studies to calculate and evaluate economic and environmental impacts. Lynch, J. et al. (2018) used the data from FBS as an input for Farmscoper to estimate the levels of nitrate, phosphorus, ammonia and greenhouse gas emissions in East Anglian cereal and South-Western dairy farms. The FBS has been used to describe the evolution of diversification in large farms in Wales and England (McNally, S. 2001). The data acquired from the FBS has been used in a variety of studies examining farm profitability (Wilson, P. 2011), performance (Wilson, P. et al. 2013) and technical efficiency (Gadanakis, Y. and Areal, F. J. 2018).

5.3. Utilised Agricultural Area (UAA)

This section of the chapter examines the Utilised Agricultural Area (UAA) in Wales and England. The UAA is the basic agricultural area. It is the total area taken up by permanent grasslands, permanent crops and arable land. The Farm Business Survey (FBS) calculates UAA by adding the area for crops and grass and fodder. The area is given in hectares. The total UAA in Wales, England and the UK is presented in Table 5.1 along with the UAA as a proportion of total land area in the UK from 2006-2015.

Table 5. 1: Utilised Agricultural Area for Wales, England and the UK (in thousand hectares) (2006-2015)

	Wales (000 ha)	England (000 ha)	UK (000 ha)	UAA as a proportion of total UK area
2006	1,679	9,298	17,896	73%
2007	1,640	9,222	17,737	73%
2008	1,634	9,261	17,703	73%
2009	1,669	8,946	17,324	71%
2010	1,709	8,873	17,234	71%
2011	1,712	8,863	17,172	70%
2012	1,748	8,925	17,189	70%
2013	1,739	9,018	17,259	71%
2014	1,811	8,962	17,240	71%
2015	1,842	8,912	17,147	70%
Total area	2,075	13,042	24,291	

Source: Wales - Welsh Government, W. (2016), England- DEFRA (2018c), UK - DEFRA (2018e)

The UAA in Wales was 1.6 million hectares in 2006 which increased to 1.8 million hectares in 2015. The total area of Wales is a little over 2 million hectares and 89% of the total area in Wales is UAA. Whereas the UAA in England declined from 9.2 million hectares in 2006 to 8.9 million hectares in 2015. The total area of England is 13 million hectares and the UAA accounts for 68% of the total area. The UAA in Wales increased approximately 10% whereas the UAA in England decreased 4% over the period of 10 years. Overall the UAA in the UK declined by 4% over the course of 10 years. The UAA covers 70-73% of the total land area in the UK. In 2015, the UAA in the UK was 17.1 million hectares covering 70% of the total land area.

The major portion of the UAA in the UK is given for cereal crops which amounts to 51% of the total area in the UK. Temporary grass came in second with 18% of the total croppable area. The remaining area is covered by horticultural crops, potatoes and other arable and uncropped arable land (DEFRA 2015a).

The number of dairy holdings and their UAA in Wales and England is presented in Table 5.2. The data taken from the FBS is from 2006 to 2015 on farms including more than 20 dairy animals (Stokes, J. R. et al. 2007). The number of farms vary over the years as old farms close or change their business practices and new farmers enter the market.

Table 5. 2: Dairy holdings, UAA and average farm size in the FBS (Wales and England)

	Wales			**England**		
	No. of holdings	**UAA (ha)**	**Average farm size (ha)**	**No. of holdings**	**UAA (ha)**	**Average farm size (ha)**
2006	127	15,148	119	322	47,431	147
2007	127	13,874	109	309	47,234	153
2008	127	15,080	119	317	49,558	156
2009	127	15,233	120	350	51,309	147
2010	124	14,971	121	350	50,982	146
2011	125	14,571	117	340	51,036	150
2012	125	14,314	115	335	51,355	153
2013	121	12,734	105	319	47,258	148
2014	122	12,993	107	320	47,107	147
2015	117	12,959	111	301	45,333	151

Source: DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The number of dairy holdings in Wales ranged from 127 in 2006 to 117 in 2015. The UAA decreased from 15,148 ha in 2006 to 12,959 ha in 2015. Due to the overall reduction in the number of dairy holdings and a reduction in UAA, the average size of the dairy farm in Wales reduced from 119 ha in 2006 to 111 ha in 2015. The average farm size was the lowest in 2013 at 105 ha.

The number of dairy holdings in England varied over the period as shown in Table 5.2, ranging from 301 to 350 holdings. The UAA of these holdings ranged from 45,333ha to 51,355 ha from 2006-2015. The average dairy farms in England were larger than those in Wales. The average farm in England was lowest in UAA in the year 2010, averaging 145 ha. This made the smallest average farm in England about 20% larger than the largest average farm in Wales in 2010. The dairy farms in England were 20-40% larger than the dairy farms in Wales. On an average, the dairy farms in England are 24% larger than the dairy farms in Wales.

5.4. Livestock and Milk produced on the farm

This section examines the livestock numbers and milk produced by these animals in Wales and England. Livestock is defined as any domesticated animal that is used for agricultural proposes like producing food. The largest number of livestock category in the UK is poultry. The UK has around 167.6 million poultry, which includes chicken, turkeys, ducks and geese. In the second place are the sheep and lambs that total to 33.3 million and a third are cattle and calves which are about 10 million. Among all the livestock categories in the UK, only the number of cattle and calves have fallen in 5 years (DEFRA 2015a).

Among all the livestock categories, our focus is mainly on the dairy animals. The total number of cows, cattle and milk produced in the UK is presented in Appendix 5.1. The total number of cows and cattle in the UK has fallen 7 % from 2006 to 2015. However, the milk production has increased almost 8%.

Table 5.3 presents the total number of dairy cows in Wales, England and the UK.

Table 5. 3: Dairy Cows (thousand dairy head, Wales and England)

	Wales (000)	England (000)	UK (000)[14]
2006	237	1,259	1,963
2007	234	1,236	1,937
2008	229	1,199	1,892
2009	221	1,163	1,838
2010	221	1,160	1,830
2011	220	1,129	1,796
2012	224	1,121	1,796
2013	223	1,113	1,782
2014	234	1,143	1,841
2015	246	1,162	1,895

Source: ADHB (2018f)

A dairy cow is referring to an animal that is of age 2 years or more has borne at least one calf. The number of dairy animals are decreasing in England and the whole of the UK whereas we see an increase in the number of dairy animal in Wales. The number of dairy cows in Wales was 237,000 cows in 2006 which increased to 246,000 cows in 2015. So, over a period of 10 years, Wales saw a 4% increase in the number of dairy cows. In contrast, the number of dairy cows in England decreased from 1,259,000 in 2006 to 1,162,000 in 2014. England saw an 8% reduction in the number of dairy cows. The number of dairy cows in the UK as a whole, decreased from 1,963,000 in 2006 to 1,895,000 in 2015.

We can observe declining trends in the number of dairy animals and cattle in the UK. Despite the decline in animal number, milk production has increased over the years as shown in Appendix 5.1. The increase in milk production is attributed to the increase in milk production per cow due to improvement in feeding practices, selective breeding(Stafford, K. J. and Gregory, N. G. 2008) and animal genetics (VandeHaar, M. J. et al. 2016). The number of dairy animals are declining in England whereas the numbers are increasing in Wales indicating that milk production is increasing in Wales. However, for this study, we will focus on the data obtained from the FBS.

[14] The total number of cows in the UK in Table 3 differs from the total number of cows in Table 3 as the cows in Table 4 are the dairy cows only reared for milk production. Whereas the total cows in Table 3 includes dairy cows raised for their meat.

The FBS provides the data on the number of dairy cows and milk produced on a farm. The amount of milk produced and the number of dairy cows provided by the FBS for Wales and England are presented in Appendix 5.2. Using the data provided in Appendix 5.2 we can derive the average herd size and the amount of milk produced in Wales and England which is presented in Table 5.4.

Table 5. 4: The average herd size and milk produced per cow in Wales and England in the FBS (2006-2015*)*

	Wales		England	
	Herd Size	**Milk Produced per cow (hl/cow)**	**Herd Size**	**Milk Produced per cow (hl/cow)**
2006	115	62	119	70
2007	123	62	124	69
2008	128	62	137	69
2009	131	60	131	70
2010	132	64	134	71
2011	134	68	137	73
2012	133	68	141	73
2013	132	65	142	71
2014	140	67	143	72
2015	152	70	152	74

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The average herd size in Welsh farms in the year 2006 was 115 cows which increased to 152 cows in 2015. The milk production per cow also increased in Wales. In the year 2006, a dairy cow was producing 62 hectolitres of milk on an average which increased to 70 hectolitres of milk in 2015. Similarly, the herd size in FBS's farms in England increased from 119 cows in 2006 to 152 cows in 2015. The milk production per cow in English farms also increased from 70 hectolitres of milk in 2006 to 74 hectolitres of milk in 2015.

The average herd size in Wales is smaller than the herd size in England in 2006. However, by 2015, the average herd size in Wales and England was the same. The dairy cows in English farms are slightly more productive than the dairy cows in Welsh farms as shown by a higher milk production per cow. However, the cows in Welsh farms are becoming more productive which was shown by a 12% increase in the amount of milk produced by Welsh dairy cows over a 10-year period compared to only 5% increase in milk production per cow in English dairy farms. The herd size has increased in both Welsh and English farms however the increase in herd size is greater in Welsh farms than English farms over a 10-year period.

5.5. Labour input

Labour is an important input in dairy farming. The proportion of labour force employed in agriculture in the UK has been persistently declining. Less than 1% of the total labour force in the UK is employed in the agricultural sector in 2011 (Devlin, S. 2016). The decline in labour involvement in agriculture has been due to unfavourable work hours, low pay and hard work (Commons, H. o. 2017) .

The labour input is denoted in hours spent working on a farm. The total hours worked includes part time and full time employees. Part-time workers are those who work on an average less than 30 hours per week on a farm. It also includes those employees who are unpaid like the farmer's spouse and possibly children or close family members. It excludes those workers who are below the age of 13 years.

The FBS characterises the work on the farm as all fieldwork, animal husbandry, maintenance work as well as administrative duties associated with the farm but excludes the work performed for the households. The hours worked on a farm are categorized according to the type of labour. The labour on a farm includes hired labour, the farmer himself and his/her spouse.

The hours worked per farm and per UAA in Wales and England from 2006 to 2015 is reported in Table 5.5.

Over the years, the average number of hours worked on a dairy farm have increased only slightly despite a large increase in the herd size. The labour hours in Welsh farms increased from 5,572 hours in 2006 to 6,303 hours by 2015. So, the Welsh farms only saw a 13% increase in the number of hours per farm over the 10-year period whereas the herd size increased 32% over the same time (Table 5.4).

Table 5. 5: Labour hours per farm and UAA in Wales and England in the FBS (2006-2015)

	Wales		England	
	Labour Hours	Labour Hours per UAA (hrs/ha)	Labour Hours	Labour Hours per UAA (hrs/ha)
2006	5,572	47	7,599	52
2007	5,707	52	7,610	50
2008	5,941	50	8,048	51
2009	5,949	50	7,703	53
2010	6,100	51	7,734	53
2011	6,002	51	7,819	52
2012	5,915	52	7,951	52
2013	5,880	56	8,034	54
2014	5,983	56	8,005	54
2015	6,303	57	8,230	55

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

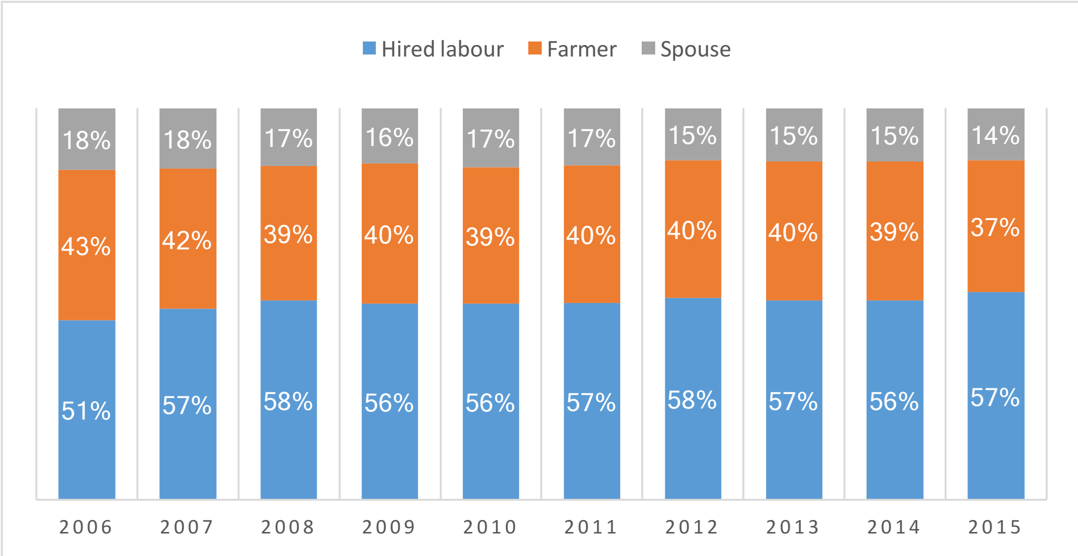
In the year 2006, a worker spent approximately 47 hours per hectare on a Welsh farm which increased to 57 hours per hectare in 2015. So, there has been a 22% increase in the hours worked per hectare in Welsh farms over a 10-year period. The increase in hours worked per hectare can be attribute to the increase in herd size on dairy farm or more intensive land use by the farm.

Similarly, the hours worked on an English farm increased from 7,599 hours to 8,230 hours. The increase in the hours worked on the farm can be attributed to the increase in the number of dairy cows on English farms (Table 5.4). The hours worked per hectare on an English farm increased from 52 hours in 2006 to 55 hours in 2015 showing a 6% increase over the 10-year period.

The hours worked per hectare differ slightly between Welsh and English farms, over the years. As the herd size in Welsh farms is increasing and the farm size is decreasing, the number of cows per hectare on the dairy farms in Wales has increased. An increase in the number of animals per hectare has led to an increase in labour hours worked per hectare.

The labour force on a farm consists of the farmer, his/her spouse and the hired labour. The share of hired labour, farmer’s hours and his/her spouse hours is shown in Figure 5.1 for Wales.

Figure 5. 1: Share of the types of labour in farms in Wales in the FBS (2006-2015)



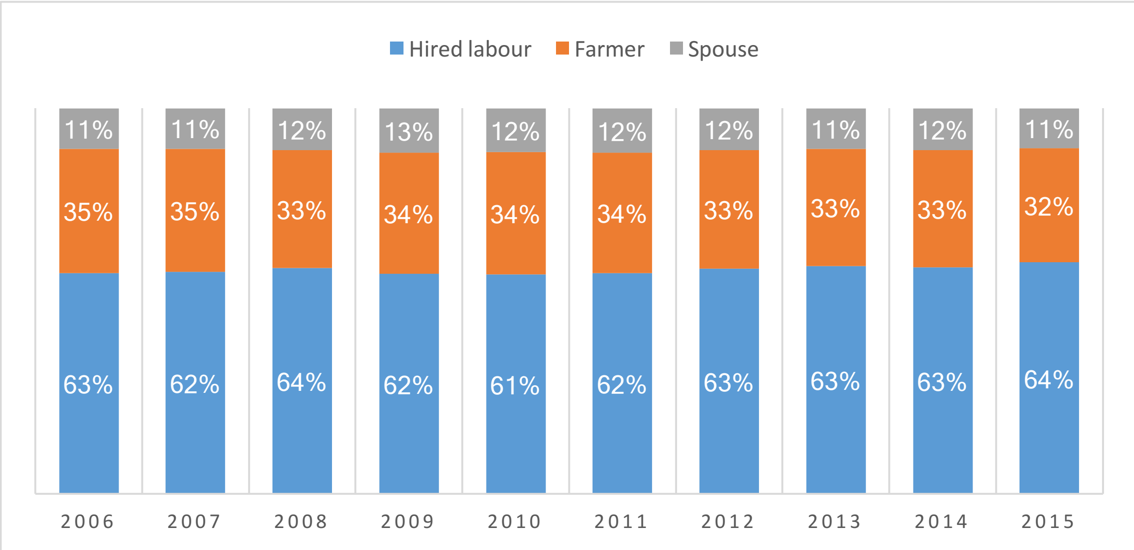
Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The hired labour works the most hours, followed by the farmer and lastly the spouse of the farmer. The hired labour worked 51% of the total hours on the farm and it increased to 57% by 2015. The farmer worked 43% of the total hours on the farm in the year 2006 which declined to 37% of the total hours by 2015. Like the farmer, the contribution of the spouse decreased from 18% in 2006 to 14% in 2015.

Thus Figure 5.1 shows that over the years, the hours worked on a farm by hired labour has increased while the hours worked by farmer and his/her spouse has decreased. The share of hired labour, farmer's hours and his/her spouse hours is shown in Figure 5.2 for England from 2006 to 2015.

Like Wales, the largest portion of work done on the English farm is by the hired labour. In England, the hired labour worked 63-64% of the total hours on the farm on an average whereas the farmer worked 32-35% of the total labour hours. The spouse, again worked the least hours on the farm, working 11-12% of the total hours on the farm.

Figure 5. 2: Share of the types of labour in farms in England in the FBS (2006-2015)



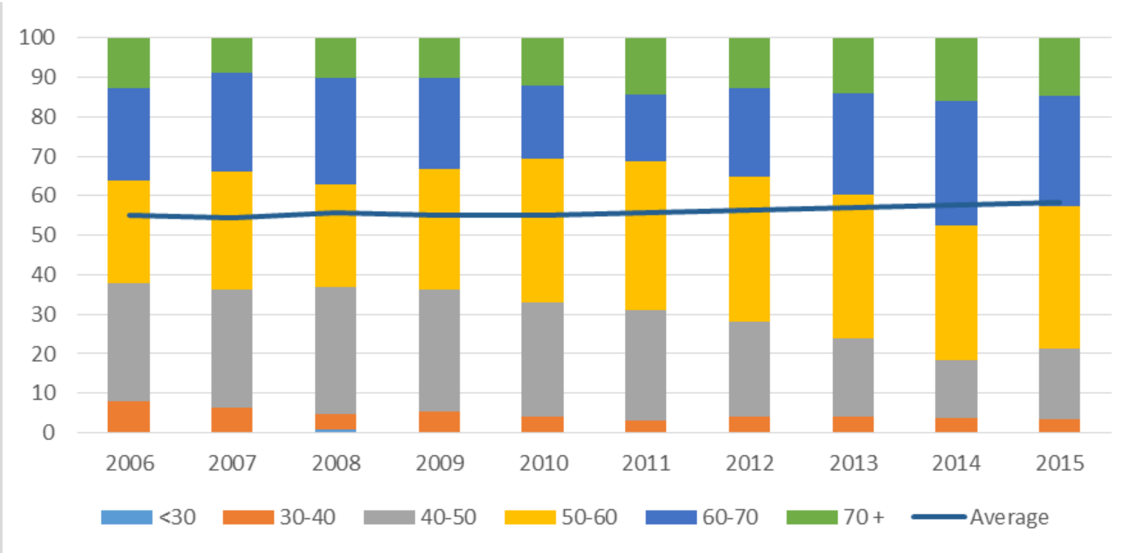
Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

Figure 5.1 and Figure 5.2 shows that the farms in England rely more on the hired labour than the Welsh farms as the proportion of hours worked by the hired labour in English farms is more than the proportion of total hours worked by hired labour on Welsh farms. The proportion of the type of labour on the England farm remained relatively unchanged over the period of 10 years. In the case of Welsh farms, the hired labour contributes more towards the working of the dairy farm indicating a shift of reliance of work from farmer and spouse to the hired labour.

5.5.1. <u>Age of dairy farmers</u>

Figure 5.3 shows the age distribution of the dairy farmers in Wales. In all the years, the farmer's age was more than 30 years with the exception in 2008 when the age of the farmer was less than 30 years. The average age of the dairy farmer in Wales has increased from 54.83 years in 2006 to 58.24 years in 2015.

Figure 5. 3: Age bracket of dairy farmers in Wales in the FBS (2006-2015)

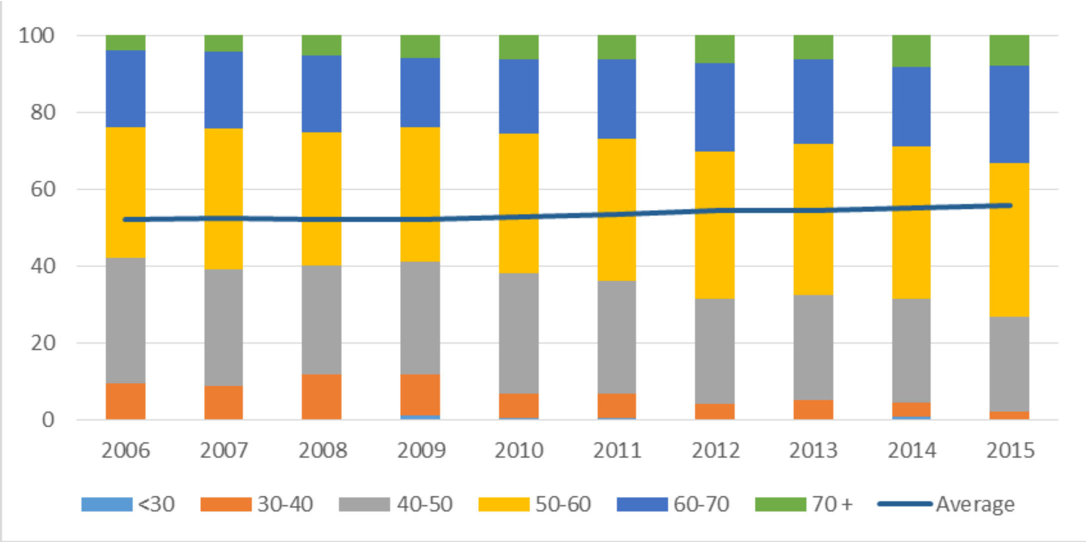


Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The largest percentage of farmers were between the ages of 40-59 years. The increasing average age of the farmers in Wales was due to the increase in the number of farmers aged 50 years and more.

Similar is the case for England shown in Figure 5.4 where the average age of a dairy farmer is also increasing. In the year 2006, the average age of a farmer was 51.94 years which rose to 55.89 years in 2015. The average farmer in Wales is approximate 3 years older than the farmer in England. Only a small number of farmers in England were aged less than 30 years. The percentage of dairy farmers aged 50 years and above has increased from 58 % in 2006 to 73 % in 2015. The portion of farmers belonging to a younger age bracket has decreased from 42% to 28 %. The largest decrease is due to reduction in farmers belonging to age bracket 30-40 years.

Figure 5. 4: Age bracket of dairy farmers in England in the FBS (2006-2015)



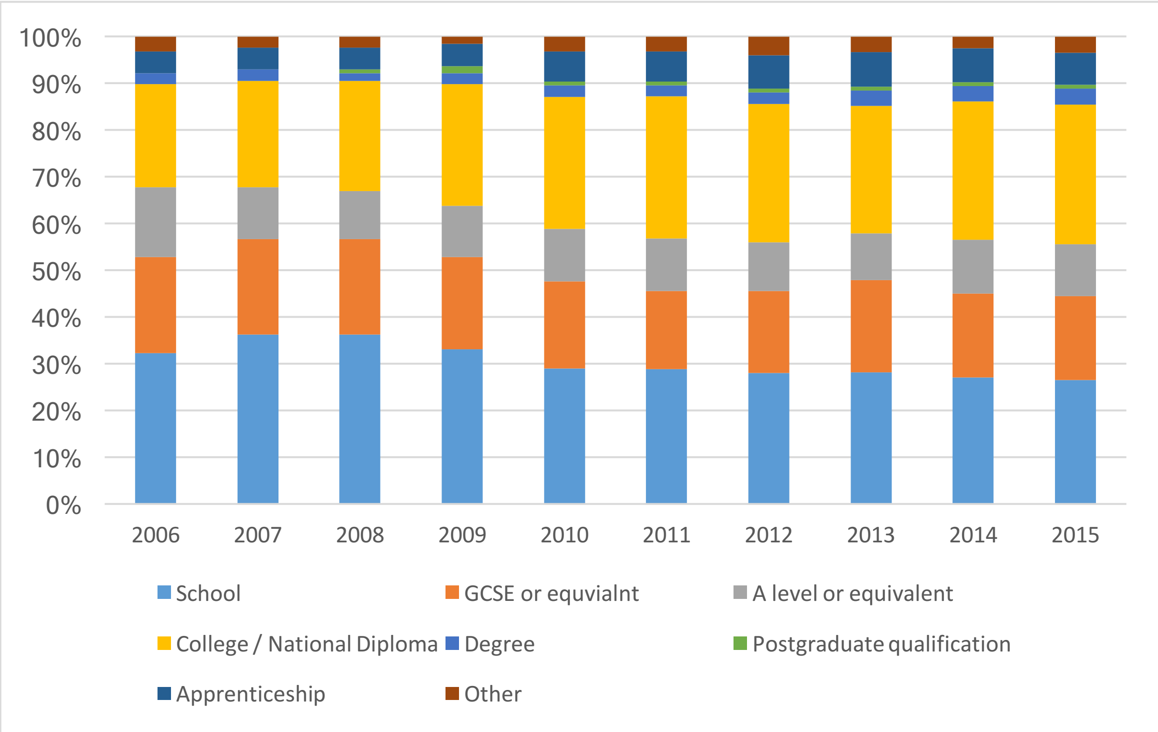
Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

5.5.2. Education

The educational qualifications of farmer, manager, and other partners is provided in the FBS. The FBS provides eight types of educational classification for the farmers: School; GCSE or equivalent; A-Levels or equivalent; College; Degree; Postgraduate Qualification; Apprenticeship and Others.

When a person has more than one qualification, the highest qualification is given. The lowest level of education is of school only. The subjects regarding agriculture are usually taught at a higher educational institution, after A-levels and the minimum entry requirement is 17 to 18 years (Gasson, R. 1998). The education level of farmers in Wales from 2006 to 2015 is presented in Figure 5.5.

Figure 5. 5*:* The education level of farmers in Wales in the FBS (2006 – 2015)

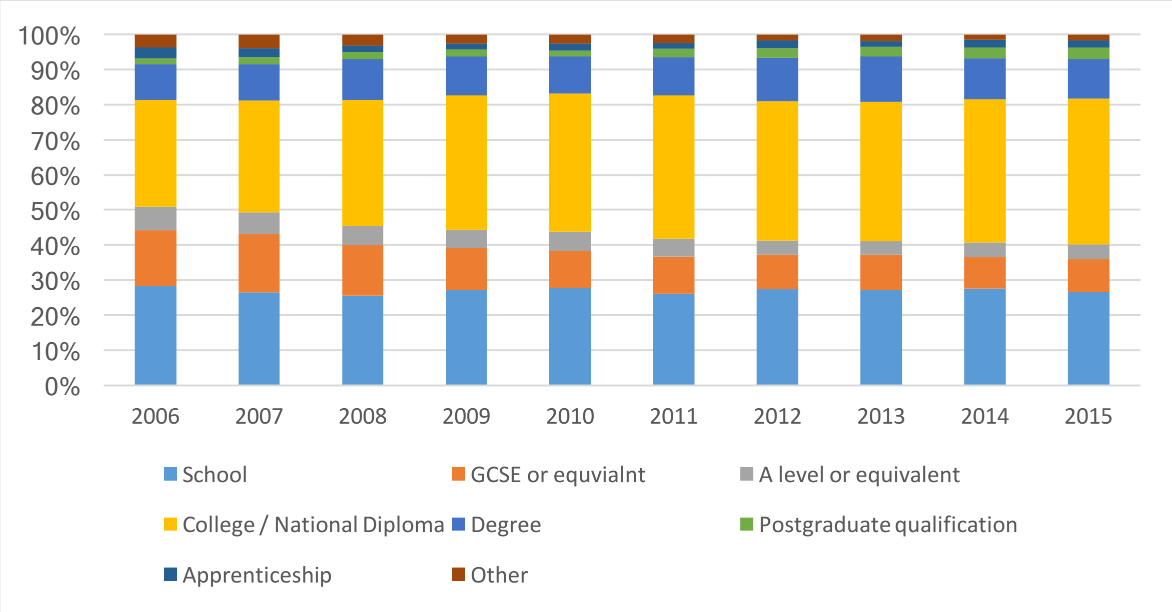


Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

In 2006, 68 % of the farmers had a high school education (A-levels or below), 24% had a college/university degree (diploma, undergraduate and postgraduate) and 5% had worked as an apprentice. But the farms sampled in the year 2015 showed that 56% of farmers had high school education (A-levels or below) and 34% had a college/university degree (diploma, undergraduate and postgraduate). Thus, over the period of 10 years, the largest increase was seen in the number of farmers going to college.

The education level of farmers in England from 2006 to 2015 is presented in Figure 5.6. Like Wales, the largest percentage of farmers in the sample had a high school education (A-levels or below). In the year 2006, approximately 50% of the farmers had a higher qualification and 42% had a college degree. However, by the year 2015 the percentage of a farmer having only higher school education declined to 42% while the percentage of a farmers having college/university degree (diploma, undergraduate and postgraduate) rose to 56%.

Figure 5. 6: The education level of farmers in England in the FBS (2006 – 2015)



Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

These results need to be analysed with caution as they represent only a small proportion of the dairy farm population in the UK. However, certain conclusions can be drawn from the results. Firstly, the level of education in dairy farms in Wales is less than the education level in the dairy farms in England. In Wales, approximately 54-64% of the farms in the sample over the years had only high school education whereas in England 40-50% of the farms had a high school education. Secondly, in both England and Wales, the level of education is rising as more and more farmers are opting for a college education as shown by the increase in the percentage of farmers having a college degrees, over the period of 10 years.

5.6. Animal Feed

Animal feed represents the expenditure on feed for the animals on the farm, thereafter referred to as just feed. Animal feed is one of the most important inputs of a dairy farm as the composition and the quantity of feed determines the amount of milk produced by the cow.

The feed variable includes the value of all cereals and other crops grown on the farm that is consumed on the farm by the animals. The feed values are given in £ and are adjusted to 2015 price level.

Table 5.6 shows the £ value that an average FBS's farm in Wales and England spends on purchasing feed. It also shows the cost of feed per cow.

Table 5. 6: Average Feed costs per farm and per cow in Wales and England in the FBS (2006-2015)

	Wales		England	
	Avg. Feed cost per farm (£)	**Cost of feed per cow (£/cow)**	**Avg. Feed cost per farm (£)**	**Cost of feed per cow (£/cow)**
2006	49,787	432	57,276	480
2007	52,580	427	63,270	509
2008	64,770	508	83,574	611
2009	80,719	617	102,124	778
2010	79,478	600	95,581	714
2011	80,125	598	96,660	705
2012	87,141	653	106,202	754
2013	93,470	707	116,750	820
2014	104,868	749	120,759	842
2015	102,676	673	118,681	779

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The expenditure on the purchase of feed largely depends on the number of animals on the farm and the price of a unit of feed. As shown in Table 5.6, the average cost of feed per farm is rising in Wales. In the year 2006, a farm on an average, spent £49,787 which increased more than 100% to £102,676 in the year 2015. One reason for an increase in the cost of feed over the years is the increase in herd size on the farm. However, it is not the only factor which contributes to the increasing feed costs per farm as when analysing the cost of feed per animal, we see that the feed costs per cow have risen over the 10-year period. In the year 2006, a farm on an average spent £432 on the cost of feed per animal which rose to £673 in the year 2015. So, we saw a 56% increase in the cost of feed per animal over the period of 10 years.

The expenditure on the feed by an average dairy in England has doubled from 2006 to 2015. The average feed cost was £57,276 per farm in 2006 that increased to £118,681 by 2015.The rising cost of feed per farm is due to the increase in herd size. However, the feed cost per cow also saw a 62% rise from 2006 to 2015. The average cost of feed per cow in the year 2006 was £480 which increased to £779 in 2015.

The increase in feed cost per animal can be attributed to the rising feed costs due to adverse weather conditions, limited supply, rising global demand for animal feed and the change in diet composition (BPEX 2007; FAO 2011; ADHB 2016).

5.7. Greenhouse Gas Emissions

The dairy farms have been identified as an important source of greenhouse gas emissions (GHG). The important GHG emitted due to dairy farming include Methane (CH_4), Nitrous Oxide (N_2O) and Carbon dioxide (CO_2). A variety of tools have been developed by educational institutions and government bodies to calculate the GHG emissions from farming. Some of these tools are Farmscoper, AgreeCalc and IMPACCT. Farmscoper (Farm Scale Optimisation of Pollutant Emission Reduction) is a Microsoft Excel-based tool developed for DEFRA by ADAS[15] that allows its users to calculate agricultural pollutants on the farms. It uses data from farms' physical and structural inputs to estimate the production of a range of pollutants at an individual farm level. The pollutant losses are calculated using IPCC methodologies for methane and nitrous oxide production (ADAS 2010).

AgReCalc (Agricultural Resource Efficiency Calculator) calculates the use of resources and GHG emissions of the whole farm or per unit of output. AgReCalc is developed by Scotland's Rural College (SRUC) which calculates emissions using IPCC Tier 1 and Tier 2 guidelines and generates a year on year comparison (Reid, G. 2015).

IMPACCT (Integrated Management oPtion for Agricultural Climate Change miTigation) is an EU project led by the University of Hertfordshire that aims to help farmers to reduce greenhouse gas emissions and reduce carbon footprint through modification of farming practices. It is easy to use farm assessment wizard with video guides to show how to work through the assessment. The emissions are calculated using IPCC guidelines and PAS 2050[16]. However, the model does go beyond IPCC guidelines to incorporate site specific factors like climate and soil type. These tools, including the ones not mentioned, use IPCC guidelines to measure emissions as it is the most comprehensive source on GHG emissions (Warner, D. et al. 2014).

[15] ADAS is a professional service that provide its clients with sustainable solutions for the environmental, agricultural and rural sector.
[16] PAS 2050 is Public Available Specification for the assessment of the life cycle greenhouse gas emissions of goods and services

All tools created to calculate GHG emissions or environmental impact use IPCC guidelines. With the farm specific information available from the FBS, emissions could be calculated for individual farms rather than using any tools created by other researchers or institutions. Thus, the GHG emissions in this study are calculated using the IPCC guidelines which is the basis for all tools available. This has been to properly understand how IPCC calculate emissions from dairy cows. Furthermore, the emissions calculated would accurately represent farms in the sample. Calculating GHG emissions from IPCC guidelines ensures that the results are transparent, consistent and precise and they reflect the management practices of that farm.

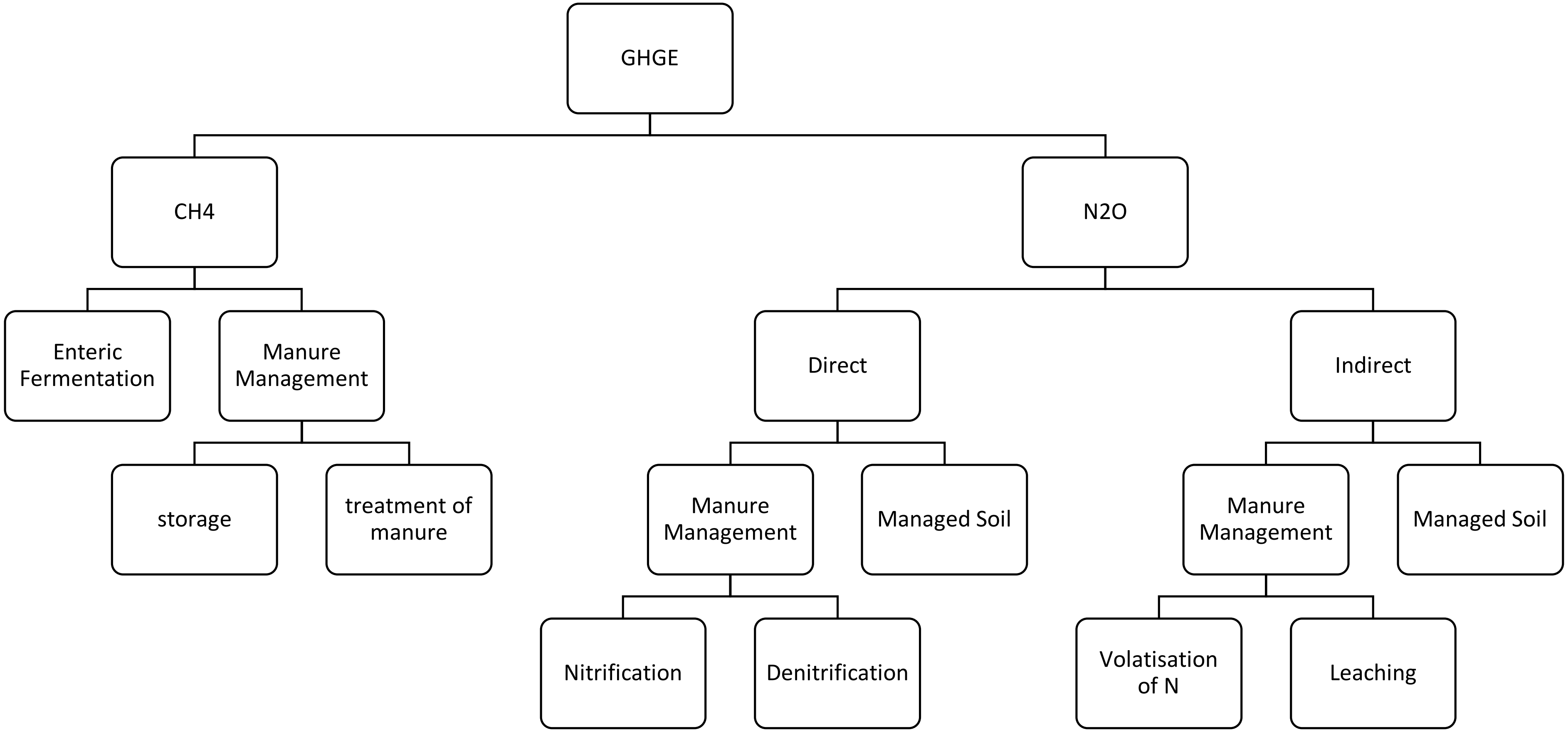
This section provides a detailed guidance on the estimation of the GHG from livestock farming. The emission of CH_4 and N_2O are calculated using the Intergovernmental Panel on Climate Change (IPCC) guidelines for National Greenhouse Gas Inventories (IPCC 2006) . The emission of Carbon dioxide (CO_2) are also emitted during farming but its emissions from livestock are not estimated. This is because the annual net CO_2 emissions are assumed to be zero as CO_2 is photosynthesised by the plants and is returned to the atmosphere as respired CO_2 (IPCC 2006).

Before calculating the GHG emissions using IPCC (2006) guidelines, there is first a need to understand how and where these emissions occur during the production process. Figure 5.7 presents a flow chart on the emissions of GHG from livestock farming.

The CH_4 is emitted by dairy farms due to the process of enteric fermentation and manure management. Cattle contribute the most to CH_4 emission from enteric fermentation due to their ruminant digestion system. The emissions of CH_4 from manure management are relatively smaller compared to its emission from enteric fermentation. The emissions from manure management occur during the storage and treatment of the manure (IPCC 2006).

The emission of N_2O are a bit more complex. The N_2O is emitted during dairy farming from direct and indirect processes. The direct and indirect emissions of N_2O are explored in detail in section 5.6.2. The direct and indirect emissions of N_2O occur during the manure management and its application to the soil. The indirect emissions of N_2O occur due to nitrogen losses from the system. A detailed explanation of the source and the calculations of CH_4 and N_2O are discussed in the next few sections of this chapter.

Figure 5. 7: Flow chart of GHGE from livestock farming



Source: (IPCC 2006)

5.7.1. Methane Emissions

Methane (CH_4) is produced because of the microbiological activity in which the animal metabolizes carbohydrates. Methane is one of the by-products of digestion and it is insoluble in water. Due to this property, methane is easily emitted from animal waste (Monteny, G. J. et al. 2001). Methane production largely depends on the animal type and size, the feed intake, and feed's composition and digestibility (Brown, P. et al. 2017).

CH_4 is emitted in dairy farming though enteric fermentation and manure management which are discussed below:

Enteric Fermentation

The type of animal's digestive system has a large impact on CH_4 emissions. Ruminant livestock like cattle, buffalo, sheep, deer and goats have an expansive chamber, called the rumen where the intensive microbial fermentation takes place. The rumen is responsible for digesting cellulose found in their diets. The fermentation of feed in the animal's digestive track is the source of CH_4 production from enteric fermentation.

Dairy animals produce higher levels of CH_4 from enteric fermentation as compared to other livestock due to high CH_4 emission rate because of their digestive process. Emissions from enteric fermentation from a livestock category is calculated using IPCC (2006) Tier 2 approach. The Tier 2 method requires detailed information on the characteristics of livestock. It is recommended to use Tier 2 approach when calculating enteric fermentation from cattle as opposed to a simplified Tier 1 approach. Tier 2 method allows us to estimate the emissions more accurately as the calculations of the emissions require more information. The CH_4 emission from enteric fermentation is calculated using the formula:

$$Emissions = EF * \left(\frac{N}{10^6}\right) \tag{5.1}$$

Where:

Emission: Methane emissions from Enteric Fermentation, Gg $CH_4 yr^{-1}$

EF: Emission factor for the livestock population kg CH_4 $head^{-1}$ yr^{-1}

N : The number of animals

The emissions of CH_4 are calculated by multiplying the population of the livestock with the emission factor of enteric fermentation. The livestock population for England and Wales is taken from the FBS. To calculate the emission factor *(EF)* from CH_4, information is needed on the feed intake of the livestock and the factor for conversion of feed to methane. Thus, *EF* is calculated by using the formula:

$$EF = \left[\frac{GE*\left(\frac{Ym}{100}\right)*365}{55.65}\right] \quad (5.2)$$

Where:

EF = Emission factor, kg CH_4 head^{-1} yr^{-1}

GE = Gross energy intake, MJ head^{-1} day^{-1}

Y_m = Methane conversion factor, per cent of gross energy in feed converted to methane

The factor 55.65 (MJ/kg CH_4) is the energy content of methane.

The Gross Energy intake (GE) is the amount of energy consumed by the animal. It is calculated using formula:

$$GE = \frac{\left(\frac{NEm+NEa+NE_l+NE_{work}+NEp}{REM}\right)+\left(\frac{NEg+NE_{wool}}{REG}\right)}{\frac{DE\%}{100}} \quad (5.3)$$

Where:

GE = Gross energy, MJ day^{-1}

NE_m= Net energy required by the animal for maintenance, MJ day^{-1}

NE_a = Net energy for animal activity, MJ day^{-1}

NE_l = Net energy required for lactation, MJ day^{-1}

NE_{work} = Net energy for work, MJ day^{-1}

Ne_p = Net energy required for pregnancy, MJ day^{-1}

REM = Ratio of net energy available in a diet for maintenance to digestible energy consumed

NE_g = Net energy needed for growth, MJ day^{-1}

NE_{wool} = Net energy required to produce a year of wool, MJ day^{-1}

REG = Ratio of net energy available for growth in a diet to digestible energy consumed

$DE\%$ = Digestible energy expressed as a percentage of gross energy

NE_m, NE_a, NE_l, NE_{work}, Ne_p, REM, NE_g, NE_{wool}, REG and $DE\%$ can be calculated using the formulas provided in IPCC (2006) however in this study, we have used the vales for various net energy requirement provided by Brown, P. et al. (2017). The calculation of these parameters requires detailed information on the feed intake of livestock to support activities such as growth, lactation, and pregnancy. The values of NE_m, NE_a, NE_l, Ne_p, REM and REG are taken from UK greenhouse gas inventory, 1990 to 2015 to calculate GE (Brown, P. et al. 2017). The variable of NE_{wool} is ignores for livestock as it calculates the energy required to produce wool. The value of GE, over the years, is provided in the report and is used for our analysis.

IPCC (2006) provides default value of DE for Western Europe for dairy cows. The DE percentage for pasture fed dairy is 55 – 75% and 75- 85% for dairy animals fed with more than 90% of concentrated diet. A country specific value for DE for dairy cows is taken for our analysis which is 74.52 % (Brown, P. et al. 2017). It is on a higher side when comparing with the IPCC (2006) default value of pasture fed animals. A higher value is acceptable as it takes an average of the diet fed to the animal during lactation and non-lactation period as well as includes the effect of concentrated and foraged feed on the animal's digestibility (Brown, P. et al. 2017). The methane conversion factor (Y_m) is 6.5% (IPCC 2006; Brown, P. et al. 2017).

Following IPCC (2006) guidelines and parameters, Brown, P. et al. (2017) calculated gross energy intake (GE) and emission factors (EF). These parameters values used for the calculations are presented in Table 5.7.

Table 5. 7: Tier 2 Enteric Fermentation Emission Factor for livestock population (kg CH_4 head^{-1})

	GE (MJ d^{-1})	EF
2006	286	123
2007	288	123
2008	286	123
2009	286	124
2010	292	126
2011	299	129
2012	297	127
2013	297	128
2014	308	133
2015	300	130

Source: Brown, P. et al. (2017)

The emission factor for enteric fermentation for dairy cows by Brown, P. et al. (2017) is higher than the default Western Europe values provided under the IPCC (2006) Tier 1 approach. The *EF* of CH_4 under Tier 1 approach given by IPCC (2006) is 117 kg CH_4 head^{-1} yr^{-1} whereas the factor calculated under Tier 2 approach by Brown, P. et al. (2017) ranges from 123 to 133 kg CH_4 head^{-1} yr^{-1}. The *GE* has increased over the years and so has the *EF* per cow.

Manure Management

Methane is also produced by the storage and the treatment of the manure. The term manure is used for both solid and liquid waste by the livestock. Manure is decomposed under anaerobic conditions during its storage. The CH_4 emissions from manure management depend on the amount of manure produced by the animal. The production of manure depends on the rate of waste produced per animal and the number of animals on the farm. The CH_4 production from manure management is also influenced by factors such as temperature, pH of the soil, and the availability of oxygen (IPCC 2006).

Using the IPCC (2006) guidelines, the emissions of methane from manure management are calculated using the formula:

$$CH_{4\,Manure} = \sum_T \left(\frac{EF * N}{10^6}\right) \tag{5.4}$$

Where:

$CH_{4\,Manure}$: CH_4 emissions from manure management for a defined population Gg CH_4year^{-1}

EF : Emission factor for the defined livestock population kg CH_4 head^{-1} year^{-1}

N : The number of animals

To calculate the CH_4 emissions from manure management, the emission factor (EF) of manure management is multiplied with the population of animals. The EF depends on animals' feed intake, manure characteristics and manure management practices by the farm.

The EF for the dairy cows is 21 kg CH_4 head^{-1} year^{-1} given by IPCC (2006). These emissions are based on the regional characteristics and the average annual temperature (°C) of the region. The annual temperature in the UK is considered cool with the average being between 10°C and 11°C. The emission factor for dairy cows is much higher than that for any other animal category and it increases with the rising temperatures.

The default Tier 1, EF is not used as it does not allow us to observe year to year changes. The EF of CH_4 under manure management is calculated by Brown, P. et al. (2017) using IPCC (2006) Tier 2 calculations. The $EF's$ used for the analysis are presented in Table 5.8.

Table 5. 8: CH_4 Manure Management Emission Factor for livestock population (2006-2015)

	EF (kg CH_4 head^{-1})
2006	16.6
2007	16.6
2008	16.6
2009	16.6
2010	16.9
2011	17.2
2012	17.0
2013	17.1
2014	17.7
2015	17.4

Source: Brown, P. et al. (2017)

The default IPCC (2006) Tier 1 emissions of CH_4 from manure management are overstated for dairy cows. The EF calculated using IPCC (2006) Tier 2 approach by Brown, P. et al. (2017) is used to accurately reflect the changes in animal weight, diet and production of the manure.

Results

The CH_4 emissions were calculated by using the framework presented by IPCC (2006) and the UK specific emission values taken from Brown, P. et al. (2017). The annual CH_4 emissions from enteric fermentation and manure management and emissions per litre of milk are presented in Table 5.9.

Table 5. 9: Annual emissions of CH_4 per farm from Enteric Fermentation and Manure management in Wales[17]

	CH_4 emissions per farm ($kg\ CH_4$)		Emissions per litre milk produced ($kg\ CO_2$ eq)		
	Enteric Fermentation	Manure Management	Enteric Fermentation	Manure Management	Total
2006	14,247	1,918	0.50	0.07	0.56
2007	15,170	2,042	0.50	0.07	0.57
2008	15,727	2,116	0.49	0.07	0.56
2009	16,209	2,173	0.51	0.07	0.58
2010	16,673	2,238	0.49	0.07	0.55
2011	17,216	2,304	0.48	0.06	0.54
2012	16,937	2,269	0.47	0.06	0.53
2013	16,836	2,256	0.49	0.07	0.55
2014	18,553	2,478	0.49	0.07	0.56
2015	19,820	2,653	0.47	0.06	0.53

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

The annual emission is given in kg CH_4 per year whereas the emissions per litre of milk produced are given in CO_2 equivalents. The CH_4 and later, N_2O emissions are converted to CO_2 equivalent emissions according to their global warming potential. Global Warming Potential (GWP) is a relative measure of how much a particular gas contributes to global warming. The baseline for GWP is 1 CO_2 molecule thus the GWP of CO_2 is equal to 1.

[17] Estimates are based on the number of dairy cows in the sample farms in Wales given in the FBS from 2006-2015

However, gases like methane and nitrous oxide have a higher level of GWP. One molecule of CH_4 has a GWP of 25 whereas the GWP for N_2O is 298 (IPCC 2007).

The CH_4 emissions per farm from enteric fermentation rose from 14,247 kg CH_4 in 2006 to 19,820 kg CH_4 in 2015. Similarly, the emissions of CH_4 per farm from manure management rose from 1,918 kg CH_4 in 2006 to 2,653 kg CH_4 in 2015.An increase in emissions per farm was expected with the increase in the number of dairy cows on the farms. The emissions per litre milk produced were then calculated and denoted in kg CO_2 equivalent to make comparison easier between the different GHGs. The total CH_4 emissions were calculated by adding the emission from enteric fermentation and manure management. To estimate the emissions per litre milk produced, the CH_4 emission in CO_2 equivalent were divided with the milk production in litres. Although the total annual CH_4 emission from enteric fermentation rose over the years, the emission per litre of milk produced, decreased. The emissions per litre of milk produced for enteric fermentation decreased from 0.50 kg CO_2 equivalent in 2006 to 0.47 kg CO_2 equivalent. Similarly, the emissions of CH_4 from manure management declined from 0.07 kg CO_2 equivalent in 2006 to 0.06 kg CO_2 equivalent in 2015. The total emission of CH_4 per litre of milk produced reduced from 0.56 kg CO_2 equivalent in 2006 to 0.53 kg CO_2 equivalent in 2015.

The annual CH_4 emissions per farm and CH_4 emissions per litre of milk produced from enteric fermentation and manure management in dairy farms in England are presented in Table 5.10 from 2006-2015.

The emissions from enteric fermentation contributed the most to the total CH_4 emissions. The emission from enteric fermentation were about 4 times more than the CH_4 emissions from manure management. The CH_4 emissions from enteric fermentation per farm rose from 14,681 kg CH_4 per year in 2006 to 19,815 kg CH_4 in 2015. The CH_4 emission from manure management per farm increased from 1,981 kg CH_4 in 2006 to 2,652 kg CH_4 in 2015.

Table 5. 10: Annual emissions of CH_4 from Enteric Fermentation and Manure management in England[18]

	CH_4 emissions per farm (kg CH_4)		Emissions per litre milk produced (kg CO_2 eq)		
	Enteric Fermentation	**Manure Management**	**Enteric Fermentation**	**Manure Management**	**Total**
2006	14,681	1,981	0.44	0.06	0.50
2007	15,319	2,062	0.45	0.06	0.51
2008	16,891	2,272	0.45	0.06	0.51
2009	16,252	2,179	0.44	0.06	0.50
2010	16,849	2,262	0.44	0.06	0.50
2011	17,609	2,051	0.44	0.05	0.49
2012	17,883	2,396	0.43	0.06	0.49
2013	18,164	2,434	0.45	0.06	0.51
2014	19,013	2,540	0.46	0.06	0.52
2015	19,815	2,652	0.44	0.06	0.50

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

The increase in total emissions of CH_4 was expected with the increasing number of dairy cows in England. However, the emissions per litre milk produced remained relatively unchanged. The CH_4 emission per litre of milk produced from enteric fermentation ranged from 0.44 to 0.46 kg CO_2 equivalents per litre milk produced. The emissions from manure management remained constant to 0.06 per litre milk produced. The total emissions of CH_4 per litre milk produced were 0.5 kg CO_2 equivalents in 2006 and in 2015.

5.7.2. Nitrous oxide Emissions

This section describes how the Nitrous oxide (N_2O) emissions are measured from manure management. The N_2O is emitted from manure during storage and its treatment before it is applied to the land as a fertiliser or used as fuel. The N_2O emissions are not directly produced like the CH_4 emissions through digestion of feed or manure. The N_2O emissions are released into the atmosphere through the process of ammonification of urea.

The emission of N_2O from livestock occurs directly and indirectly. The direct emissions are due to nitrification and denitrification of nitrogen in manure. Nitrification is a process in which

[18] Estimates are based on the number of dairy cows in the sample farms in England given in the FBS from 2006-2015

nitrogen compounds like ammonium (NH_4^+) are oxidized to from nitrite (NO_2^-) and nitrate(NO_3^-).

$$NH_4^+ \rightarrow NO_2^- \rightarrow NO_3^-$$

This is an aerobic process that requires the presence of sufficient supply of oxygen. An increase in the levels of nitrite and nitrate degrades water quality by reducing alkalinity and pH of water (EPA 2002). Denitrification occurs when nitrites and nitrates are transformed into N_2O (Monteny, G. J. et al. 2001).

$$NO_3^- \rightarrow NO_2^- \rightarrow N_2O$$

Denitrification is an anaerobic process that occurs naturally. Thus, the direct production of N_2O is a two-stage process.

The indirect emissions result from nitrogen losses in the form of ammonia and NO_x. These losses start from the excretion of waste in the animal houses and continue throughout the site.

The Tier 1 method is employed to measure the N_2O emissions. The total amount of nitrogen excreted by the animal in a farm is multiplied by an emission factor for the type of manure management system. The emissions are then summed for all the manure management systems. The IPCC (2006) Tier 1, guidelines provide default values of N_2O emission factor, nitrogen excretion data and manure management system.

The N_2O is directly emitted from manure management systems and the application of manure to the soil. The calculations of direct N_2O emissions are described in detail in the next few sections. The indirect emissions of N_2O from agriculture consist of five different sources (Nevison, C. 2001):

- Volatilisation and subsequent atmospheric deposition of NH_3 and NO_x
- Nitrogen leaching and runoff
- Human consumption of crops followed by sewage treatment
- Formation of N_2O in the atmosphere from NH_3
- Food processing.

In this section, the indirect N_2O emissions are estimated. Due to lack of information available on farm specific factors the indirect emissions of N_2O from atmospheric conversion of NH_3 and food processing are not included. We focus on indirect N_2O emissions from volatilisation and leaching.

Direct N_2O emissions from manure management

The direct N_2O emissions from manure management occur during the storage and the treatment of manure. The emissions depend on the storage method and the duration of storage. The direct N_2O emissions from manure management are calculated by multiplying the total amount of N excreted in different management systems by an emission factor. The country specific N excretion rates are used. The emissions are summed for all the manure management systems on a farm. The direct emissions of N_2O are calculated using the formula:

$$N_2O_{D(mm)} = \left[\sum_S [\sum_T (N * Nex * MS_S)]\, EF_{3(S)}\right] * \frac{44}{28} \tag{5.5}$$

Where:

$N_2O_{D(mm)}$: Direct N_2O emissions from manure management, kg N_2O

N : The number of animals

Nex: Annual average N excretion per head of livestock, kg N animal^{-1}

MS_S: Fraction of total annual N excretion that is managed in manure management system S

$EF_{3(S)}$: Emission factor for direct N_2O emissions from manure management system S, kg N_2O – N/kg N in manure management system S

$\frac{44}{28}$: Conversion of $(N_2O\text{-}N)_{(mm)}$ emissions to $N_2O_{(mm)}$ emissions

The livestock numbers (N) are taken from the FBS. A Tier 1 approach is used to calculate the annual N excretion rates (Nex):

$$Nex = N_{rate} * \frac{TAM}{1000} * 365 \tag{5.6}$$

Where:

Nex : Annual average N excretion per head livestock, kg N animal^{-1}

N_{rate}: Default N excretion rate kg N

TAM: Typical mass for livestock, kg animal^{-1}

The nitrogen excretion rate (Nex) depends on the nitrogen intake and retention of the animal. The nitrogen intake of an animal depends on the amount of feed consumed and the protein content of the feed. The nitrogen retention is the measure of animal's efficiency of converting animal feed to animal protein.

The values of nitrogen excretion rate (N_{rate}) and average mass of livestock (*TAM*) are taken from Brown, P. et al. (2017). The N_{rate} and *TAM*'s values are given in Table 5.11.

Table 5. 11: N excretion rate and weight of livestock

	$\boldsymbol{N_{rate}}$ (kg N)	TAM (kg animal^{-1})
2006	0.32	629
2007	0.32	640
2008	0.32	631
2009	0.33	632
2010	0.34	637
2011	0.35	636
2012	0.34	626
2013	0.34	629
2014	0.35	648
2015	0.36	608

Source: Brown, P. et al. (2017)

The N_{rate} and *TAM* of the dairy cows varies over the years. MS_S is the fraction of the manure management systems used on the dairy farms. There are four main systems of manure management used in the UK.

Table 5.12 provides percentage of various systems used for manure management in the UK and their emission factor.

Table 5. 12: Manure Management System % and $EF_{3(s)}$

MMS	%	$EF_{3(s)}$ kg N_2O per kg N excreted
Liquid/Slurry	37.30%	With crust: 0.005 Without crust: 0
Solid Storage	10.40%	0.005
Pasture/range/ paddock	48.20%	0.02
Daily Spread	4.10%	0

Source : Brown, P. et al. (2017)

The widely-used method of manure management in the UK was of pasture/range and paddock. In this system, the manure from animals is allowed to stay where it is and is not managed. The emission factor from pasture/range/paddock is 0.02 kg N_2O per kg N excreted. The second widely used method of manure management was of liquid/slurry in which the manure is stored in tanks as it is excreted. The emission factor for liquid/slurry depends on the formation of the crust. With the natural crust[19] formation, the emission factor is equal to 0.005 kg N_2O per kg N excreted however, without a natural crust cover, the emissions are considered negligible due to low potential of occurrence of nitrification and denitrification IPCC (2006).

The third method used was of solid storage. In solid storage, the manure is stored for a period of several months in piles or stacks. The manure can be stacked in piles due to loss of moisture. The emission factor for solid storage is 0.005 kg N_2O per kg N excreted The last method is of daily spread where the manure is applied to cropland or pasture within 24 hours of excretion (IPCC 2006). Emission factor for N excretion $EF_{3(S)}$ is 0 for daily spread as the emissions are negligible due to low potential of occurrence of nitrification and denitrification.

The direct emissions of N_2O from manure management for farms in Wales were calculated and the results are presented in Table 5.13.

The emissions are given in kg N_2O per year per farm for all the different types of manure management systems. The N_2O emission are the most from pasture/range/paddock as it is the most widely used type of manure management system in Wales and in the rest of the UK. Secondly, the emissions from this kind of manure management system were also more as the emission factor was the highest for this system.

[19] Cattle slurries build up a natural crust of floating organic materials on top of the liquid/slurry tanks. It is only formed if the dry matter is high enough.

The emissions of N_2O from Pasture/range/paddock ranged from 131 kg N_2O to 176 kg N_2O per farm from 2006 to 2015. The emission from pasture/range/paddock were followed by the emissions from the liquid/slurry with the natural crust formation where the N_2O emission ranged from 25kg N_2O to 34 kg N_2O over the period of 10 years. The emissions from solid storage ranged from 7 kg N_2O to 9 kg N_2O per year. The N_2O emission from the manure management system of dairy spread were 0 as the emission factor was zero. The general trend was an increase in emissions from all types of manure management systems.

Table 5. 13: Direct N_2O emissions from Manure Management Systems in Wales (2006-2015)[20]

	Manure Management System				Total (kg N_2O)	N_2O emissions per litre of milk produced (kg CO_2 eq)
	Liquid/ Slurry (kg N_2O)	Solid Storage (kg N_2O)	Pasture/ range/ paddock (kg N_2O)	Dairy Spread (kg N_2O)		
2006	25	7	131	0	163	0.068
2007	27	8	139	0	174	0.068
2008	28	8	142	0	177	0.066
2009	29	8	151	0	188	0.071
2010	31	9	159	0	198	0.069
2011	32	9	165	0	206	0.068
2012	30	8	157	0	196	0.065
2013	30	8	156	0	195	0.067
2014	34	9	176	0	219	0.069
2015	32	9	164	0	205	0.057

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

The average direct N_2O emissions per farm in Wales from manure management systems rose from 163 kg N_2O in 2006 to 205 kg N_2O in 2015. The increase in the emission per farm can be attributed to the increase in the number of animals on the farms in Wales over the years. The emission per litre milk produced are given in CO_2 equivalents. These emissions decreased from 0.068 kg CO_2 equivalent in 2006 to 0.057 kg CO_2 equivalent in 2015.

The direct N_2O emissions per farm from manure management systems in England are listed in Table 5.14.

[20] Estimates are based on the number of dairy cows in the sample farms in Wales given in the FBS from 2006-2015

As in Wales, the widely-used manure management system for dairy farms in England is also pasture/range/paddock. Since this type of manure management system had the highest emissions factor, the N_2O per farm were the highest for this type of system. The N_2O emissions from pasture/range/paddock ranged from 133 kg N_2O to 180 kg N_2O over the period of 10 years. Second highest emissions were for liquid/slurry which rose slightly from 26 kg N_2O in 2006 to 32 kg N_2O in 2015. The emission of N_2O from solid storage in 2006 was 7 kg N_2O which increased to 9kg N_2O by 2015. The total N_2O emissions per farm in England rose from 166 kg N_2O in 2006 to 205 kg N_2O in 2015. The increase in the N_2O emissions is due to the increase in the herd size on farms in England.

Table 5. 14: Direct N_2O emissions from Manure Management Systems in England (2006-2015)

	Manure Management System				Total (kg N_2O)	N_2O emissions per litre of milk produced (kg CO_2 eq)
	Liquid/ Slurry (kg N_2O)	Solid Storage (kg N_2O)	Pasture/ range/ paddock (kg N_2O)	Dairy Spread (kg N_2O)		
2006	26	7	133	0	166	0.059
2007	27	8	141	0	175	0.061
2008	30	8	153	0	191	0.060
2009	29	8	151	0	189	0.061
2010	31	9	160	0	200	0.063
2011	28	8	147	0	183	0.055
2012	32	9	166	0	207	0.060
2013	33	9	168	0	210	0.062
2014	35	10	180	0	224	0.065
2015	32	9	164	0	205	0.054

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

Despite an increase in the emission of direct N_2O per farm from all manure management systems, the emissions per litre milk produced has reduced slightly. The emissions per litre milk produced fell from 0.059 kg CO_2 equivalent to 0.054 kg CO_2 equivalent. The N_2O emissions per litre of milk produced were higher in Wales than in England.

Direct N_2O emissions from Managed Soils

The N_2O is also directly emitted from managed soils. After the treatment and storage of the manure, it is then applied to the land. The emissions that arise from the application of manure to the soil are calculated in this section.

The direct emissions of N_2O from managed soils are calculated using IPCC (2006)Tier 1 approach. The Tier 1 approach is used as there is a lack of data available for the land cover and soil type. The following N sources are used to calculate emission under the Tier 1 approach: Synthetic N fertilisers; Organic N fertilisers that include animal manure, compost etc.; N in crop residue; and Urine and dung N deposited by grazing animals on pasture.

Due to lack of availability of the data, a modified version of the Tier 1 approach has been used which only measures emissions from synthetic fertiliser and animal manure applied to the soil. To measure direct N_2O emissions from managed soil, we have equation from IPCC (2006) guidelines:

$$N_2O_{Direct} - N = (F_{SN} + F_{ON})EF_1 \tag{5.7}$$

Where:

$N_2O_{Direct} - N$: Annual direct N_2O –N emissions produced from managed soils, kg N_2O-N

F_{SN} : Annual amount of synthetic fertiliser N applied to soils, kg N

F_{ON} : Annual amount of animal manure and other organic N applied to soils, kg N

EF_1: Emission factor for N_2O emissions from N inputs, kg N_2O-N (kg N input)$^{-1}$

The amount of synthetic fertiliser N applied to soil (F_{SN}), depends on the N content in fertiliser and size of the area on which it has been applied. The synthetic fertilisers are applied to the crops and on the grazing area used by the animals. The area of a dairy farm in England is 50-60% covered with permanent grass used for grazing. Other crops to grow in those dairy farms include winter wheat, spring barley and winter barley.

To calculate F_{SN}, the percentage of area of the farm used to grow crops and permanent grass is calculated using data provided by DEFRA (2017b). The kilograms per hectare of N content of synthetic fertiliser applied to different crops and grasslands is provided by Brown, P. et al.

(2017). So F_{SN} is equal to the area of the crop and grass production on a farm multiplied by the N content kilograms per hectare of synthetic fertiliser applied on that area.

DEFRA (2017b) provides information on the total area of a dairy farm used for growing crops for animal feed. The major crops grown on dairy farms in England are winter wheat, winter barley and spring barley. The area used for growing crop was divided by the total area of the dairy farm to get a percentage of all the area reserved for growing crops and permanent grass. This percentage changes on a yearly basis however; the change is not a large one.

The percentage of area on which crops are grown is then multiplied by the utilised agricultural area (UAA) of farms in our sample to get an estimate of the area of a single dairy farm on which crops are grown. Then that area is multiplied by the kilograms of N content in synthetic fertiliser per hectare to estimate the amount of total synthetic fertiliser applied to the soil.

DEFRA (2017b) does not provide the percentage of area on which crops are grown on a Welsh dairy farm. So, to calculate the use of synthetic fertiliser, F_{SN}, we have only taken the area of permanent grass given in the FBS. Due to this, the estimates of N_2O from managed soil in Wales are understated.

The annual amount of animal manure and other organic N applied to soils (F_{ON}) is calculated by first estimating the amount of animal manure N available for application on managed soil in a farm (N_{MMS_Avb}). The following equation is used to construct N_{MMS_Avb}:

$$N_{MMS\_Avb} = \sum_S \left[\sum_{(T)} \left[\left(N * Nex * MS_{(S)}\right) * \left(1 - \frac{Frac_{LossMS}}{100}\right)\right] + \left[N * MS_{(S)} * N_{beddingMS}\right]\right] \quad (5.8)$$

Where:

N_{MMS_Avb} : Amount of managed manure nitrogen available for application to managed soil or for feed, fuel or construction purposes, kg N

N: The number of animals

Nex: Annual average N excretion per head of livestock, kg N animal^{-1}

$MS_{(S)}$: Fraction of total annual N excretion for each livestock that is managed in manure management system S

$Frac_{LossMS}$: Amount of managed manure nitrogen for livestock that is lost in manure management system S, %

$N_{beddingMS}$: Amount of nitrogen from bedding, kg N animal^{-1}

N , Nex and $MS_{(S)}$ have been discussed in detail in the previous sections.

Default values for the percentage of managed manure *N* for livestock lost in manure management system ($Frac_{LossMS}$) is used which is presented in Table 5.15.

Table 5. 15: Percent of total N loss from manure management ($\mathbf{Frac_{LossMS}}$)

Manure Management System	$Frac_{LossMS}$
Liquid/ Slurry	40 %
Daily Spread	22%
Solid Storage	40%
Pasture/range/paddock	0

Source: IPCC (2007)

The liquid/slurry and solid storage are responsible for the highest percentage of N losses from manure management systems. Both these methods led to a 40% loss in N excreted though animal manure. The amount of N contained in organic bedding material ($N_{beddingMS}$) for dairy cows in 7 kg N animal^{-1} and for other cattle is 4 kg N animal^{-1}.

The amount of manure N available for soil application used for feed, fuel or construction purposes. However, we do not have the data for the fraction of manure used for these purposes so we assume that all the manure N available is equal to the annual amount of organic fertiliser N applied to soil.

$$N_{MMS\_Avb} = F_{ON} \tag{5.9}$$

The emission factors to estimate direct N_2O emission from managed soils have been taken from IPCC. EF_1, the factor for emissions from fertiliser because of loss of soil carbon is 0.01 kg N_2O-N(kgN)$^{-1}$.

The conversion of N_2O –N emission to N_2O emission is perform using the following equation IPCC:

$$N_2O = N_2O - N * \frac{44}{28} \tag{5.10}$$

The annual direct N_2O emissions from managed soils is presented in Table 5.16 for both Wales and England.

Table 5. 16: Direct N_2O emissions from Managed Soils, Wales and England (2006-2015)

	Annual Emissions (kg N_2O)		Emissions per litre milk produced (kg CO_2 eq)	
	Wales	England	Wales	England
2006	258	329	0.107	0.118
2007	270	329	0.106	0.114
2008	274	325	0.103	0.103
2009	286	324	0.108	0.105
2010	293	341	0.102	0.107
2011	297	307	0.098	0.092
2012	286	344	0.094	0.099
2013	282	347	0.098	0.102
2014	306	355	0.097	0.102
2015	299	338	0.084	0.090

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

The annual emission of N_2O are given in kg N_2O while the emissions of N_2O per litre milk produced are given in CO_2 equivalent. The annual emissions of N_2O in Wales ranged from 258 kg N_2O in 2006 to 299 kg N_2O by 2015. The annual average N_2O emissions in England were 329 kg N_2O in 2006 to 338 kg N_2O in 2015. The annual direct N_2O emission are higher for England than for Wales.

The emission per litre milk produced are also higher for England. The Welsh farms produced 0.107 kg CO_2 equivalent emissions 2006 which reduced to 0.084 kg CO_2 equivalent emissions in 2015. In England, the emissions of N_2O ranged from 0.118 kg CO_2 equivalent in 2006 to 0.09 kg CO_2 equivalents in 2015. Emissions per litre milk produced are lower for Wales due to lack of availability of data on crop area where synthetic fertilisers are applied.

Indirect emissions of N_2O emissions due to volatilisation of NH_3 and NO_x

The indirect emission of N_2O are due to N losses in the form of ammonia and NOx. The indirect emissions of N_2O is calculated by multiplying the amount of N excreted and managed by livestock category by a fraction of volatilised nitrogen. The N losses are then summed for all manure management systems. The indirect N_2O emissions due to volatilisation of N from manure management is calculated using the formula given in IPCC (2006):

$$N_2O_V = \left(\sum_S \left[\sum_T \left[\left(N * Nex * MS_{(S)}\right) * \left(\frac{Frac_{GasMS}}{100}\right)_{(S)}\right]\right] * EF_4\right) * \frac{44}{28} \qquad (5.11)$$

Where:

N_2O_V: Indirect N_2O emissions due to volatilization of N from manure management, kg N_2O

N : The number of animals

Nex: Annual average N excretion per head of livestock, kg N animal^{-1}

$MS_{(S)}$: Fraction of total annual N excretion for each head of livestock that is managed in manure management system S

$Frac_{GasMS}$: Percent of managed manure N for livestock that volatilises as ammonia and NO_x in the manure management system S, %

EF_4: Emission factor for N_2O emission from atmospheric deposition of nitrogen on soil and water surface, kg N_2O – N (kg NH_3-N + NO_x-N volatilised)$^{-1}$

The average N excreted (Nex) is calculated in the previous section by using Equation 5.6. The fraction of total annual N excreted ($MS_{(S)}$) is given in Table 5.12.

The percentage of managed manure *N* for livestock that volatilizes as ammonia and NO_x is taken from IPCC (2006) guidelines and is presented in Table 5.17.

Table 5. 17: Percent of managed manure N that volatilises as ammonia and NO_x ($\mathbf{Frac_{GasMS}}$)

Manure Management System	$Frac_{GasMS}$
Liquid/ Slurry	40 %
Daily Spread	7%
Solid Storage/deep litter	30%
Pasture/range/paddock	0%

Source: IPCC (2006)

The largest percentage of manure *N* that volatilises is from liquid/slurry followed by solid storage. The manure management system of pasture/range a/paddock has 0% of manure N loss due to volatilisation as all the manure is spread on the soil and so all the emissions of N_2O are categorised under direct N_2O emissions from manure management systems.

Default values are used for EF_4 which is 0.01 kg N_2O – N (kg NH_3-N + NO_x-N volatilised)$^{-1}$ (IPCC 2006).

The indirect N_2O emissions per farm and per litre of milk produced due to volatilization for Wales and England are presented in Table 5.18.

Table 5. 18: Indirect N_2O emissions per farm and per litre of milk produced due to volatilization for Wales and England (2006-2015)

	Wales		England	
	Indirect N_2O (kg N_2O)	N_2O emissions per litre of milk produced (kg CO_2 eq)	Indirect N_2O (kg N_2O)	N_2O emissions per litre of milk produced (kg CO_2 eq)
2006	25	0.010	25	0.009
2007	26	0.010	27	0.009
2008	27	0.010	29	0.009
2009	29	0.011	29	0.009
2010	30	0.011	30	0.010
2011	31	0.010	28	0.008
2012	30	0.010	32	0.009
2013	30	0.010	32	0.009
2014	33	0.011	34	0.010
2015	31	0.009	31	0.008

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

The indirect N_2O emissions due to volatilisation per farm in Wales and England ranged from 25 kg N_2O to 31 kg N_2O from 2006-2015. The indirect emissions per litre of milk produced ranged from 0.009 kg CO_2 equivalent to 0.011 kg CO_2 equivalent from 2006-2015. Similarly, in England, the indirect emissions from volatilization was 0.009 kg CO_2 equivalents in 2006 which reduced to 0.008 kg CO_2 equivalents in 2015. The indirect N_2O emissions from different manure management systems in Wale s and England is given in the Appendix 5.3. The manure management system of liquid/slurry produces the most indirect N_2O as the percentage of manure N lost was the highest in this system. An overall increase was seen in the annual indirect N_2O emission per farm over the years but the emissions per litre milk produced reduced in both Wales and England.

Indirect emissions of N_2O emissions due to leaching

Nitrogen is also lost from manure management systems through leaching into the soil. The greatest N loss due to runoff is in area where there is high rainfall. The indirect N_2O emissions from leaching and runoff of N (N_2O_L)is calculated according to IPCC (2006) guidelines using the equation:

$$N_2O_L = \left(\sum_S \left[\sum_T \left[\left(N * Nex * MS_{(S)}\right) * \left(\frac{Frac_{Leach}}{100}\right)_{(S)}\right]\right] * EF_5\right) * \frac{44}{28} \qquad (5.12)$$

Where:

N_2O_L: Indirect N_2O emissions due to leaching and runoff from manure management in the country, kg N_2O

N : The number of animals

Nex: Annual average N excretion per head of species in the country, kg N $animal^{-1}$

$MS_{(S)}$: Fraction of the total annual N excretion for each livestock head that is managed in manure management system S in the country

$Frac_{Leach}$: Percent of managed manure nitrogen losses for livestock due to runoff and leaching in the manure management system S, %

EF_5: Emission factor for N_2O emission from nitrogen leaching and runoff, kg N_2O – N/kg N leached and runoff

The calculations and default values for N, Nex (Equation 5.6) and $MS_{(S)}$ (Table 5.12) have been provided in previous section. A country specific value of $Frac_{Leach}$ is used for all manure management system. $Frac_{Leach}$ taken for all manure management systems over the years is 0.03% (Nicholson, F. et al. 2011; Brown, P. et al. 2017) and the emission factor for N_2O emissions due to leaching and runoff (EF_5) is 0.0075 (IPCC 2006).

Table 5.19 presents the indirect N_2O produced per farm and per litre of milk due to leaching and runoff in Wales and England.

Table 5. 19: Indirect emissions of N_2O emissions per farm and per litre milk produced due to leaching, Wales and England (2006-2015)

	Wales		England	
	Indirect N_2O (kg N_2O)	**N_2O emissions per litre of milk produced (kg CO_2 eq)**	**Indirect N_2O (kg N_2O)**	**N_2O emissions per litre of milk produced (kg CO_2 eq)**
2006	2.51	0.001	2.56	0.001
2007	2.68	0.001	2.60	0.001
2008	2.74	0.001	2.90	0.001
2009	2.91	0.001	3.17	0.001
2010	3.05	0.001	3.35	0.001
2011	3.17	0.001	2.98	0.001
2012	3.02	0.001	3.32	0.001
2013	3.00	0.001	3.23	0.001
2014	3.38	0.001	3.44	0.001
2015	3.83	0.001	3.58	0.001

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

Total indirect N_2O emissions range from 2.51 kg N_2O to 3.83 kg N_2O in Wales and 2.56 kg N_2O to 3.58 kg N_2O in England from 2006-2015. The indirect N_2O emissions per litre milk produced ranged from 0.001 kg CO_2 equivalent over all the years for both Wales and England.

The indirect N_2O emissions due to leaching from different manure management system is given in Appendix 5.4. The manure management system of pasture/ range/paddock contribute the most to indirect N_2O emission due to leaching and runoff. Overall, the indirect N_2O emissions due to leaching and runoff are increasing over the years for all manure management system types but the emissions per litre milk produced have decreased slightly.

5.7.3. Total GHG emission

The emissions of methane and nitrous oxide were calculated in the previous section using IPCC (2006) guidelines. This section provides the total CO_2 equivalent emission per litre milk produced. The emissions from CH_4 include the emission due to enteric fermentation and manure management. The emission of N_2O include direct and indirect emissions. The direct emissions include emissions from manure management and managing soils whereas the indirect emissions of N_2O include emissions due to volatilization of ammonia and emissions due to leaching and runoff.

In this study, the calculations of emissions are focused on the dairy animal. Emissions from electricity or fuel have not calculated in this study. The direct emission of N_2O from managed soils has been calculated using IPCC guidelines. The indirect emissions of N_2O from managed soils have not been calculated due to the lack of availability of data required for those specific calculations.

The direct emissions of N_2O from managed soils depend on the synthetic fertilizer and animal manure applied to the soil. According to IPCC (IPCC 2006), there are other sources from managed soils such as N from crop residue including N-fixing crops and forage/pasture renewal returned to soils and N mineralisation associated with loss of soil organic matter resulting from changing land use or management on mineral soils. However, these two sources have not been included in this study due to lack of data available in the FBS. Furthermore, the emissions calculations from organic manure require the data for sewage sludge and compost applied to the soil but since the data is not available in the FBS, it has not been included in the study. So, the N_2O emission from organic manure assumes that all the manure has been applied to the soil.

The emissions of CH_4 and N_2O per litre milk are presented in Table 5.20 for Wales and England. These emissions are denoted in kg CO_2 equivalent. As mentioned before, the GWP is highest for N_2O, which is equal to 289 times whereas the GWP for CH_4 is 25 (IPCC 2007). However, the CO_2 equivalent emissions are higher for CH_4 compared to N_2O.

Table 5. 20: Total GHG emission in CO_2 equivalent per litre milk produced for Wales and England (2006-2015)

	Wales (kg CO_2 eq per litre)			**England (kg CO_2 eq per litre)**		
	CH_4	**N_2O**	**Total**	**CH_4**	**N_2O**	**Total**
2006	0.56	0.19	0.75	0.50	0.19	0.69
2007	0.57	0.19	0.76	0.51	0.19	0.70
2008	0.56	0.18	0.74	0.51	0.17	0.68
2009	0.58	0.19	0.78	0.50	0.18	0.68
2010	0.55	0.18	0.74	0.50	0.18	0.68
2011	0.54	0.18	0.72	0.49	0.16	0.65
2012	0.53	0.17	0.70	0.49	0.17	0.66
2013	0.55	0.18	0.73	0.51	0.17	0.68
2014	0.56	0.18	0.74	0.52	0.18	0.70
2015	0.53	0.15	0.68	0.50	0.15	0.65

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

The CH_4 emissions per litre milk produced were higher than N_2O emissions when converted to CO_2 equivalents. The CH_4 emissions decreased from 0.56 kg CO_2 equivalents in 2006 to 0.53 kg CO_2 equivalents in 2015. Similar trend was seen for N_2O emissions where the emissions of N_2O per litre milk produced declined from 0.19 kg CO_2 equivalents in 2006 to 0.15 kg CO_2 equivalent in 2015. Thus, the total emissions per litre milk produced decreased in Wales over the sample years.

The emissions of CH_4 per litre milk produced in England were around 0.50 kg CO_2 equivalents over the sample period. The emissions of N_2O per litre milk produced ranged from 0.19 kg CO_2 equivalent to 0.15 kg CO_2 equivalent over the period of 10 years. The total emissions per litre milk produced decreased in England for the sample period. These emissions decreased from 0.69kg CO_2 per litre milk in 2006 to 0.65 kg CO_2 equivalent per litre milk produced in 2015. Therefore, there was a 5% decrease in emission per litre milk produced from 2006 to 2015 in England.

Due to the lack of availability of farm-specific data in the FBS, the N_2O emissions might be different compared to literature as not all the sources of N_2O emissions have been explored in this study. Our results showed that N_2O emission for Wales and England, for the farms in the sample, over the 10-year period fell between 0.15-0.19 kg CO_2 equivalent per litre milk whereas a study on 415 UK dairy farms calculated N_2O emissions to be 0.185 kg CO_2 equivalent per litre milk (DairyCo 2014). So, even though not all measures of N_2O emissions are explored in this, the average emissions per litre of milk are similar to the ones in the literature. This is probably because only 15% of the total GHG emissions (DairyCo 2014) from dairy farming are due to N_2O emissions (DairyCo 2014) and a large portion of these emissions are have been included in this study. Due to this, the calculation of N_2O emissions in this study may not differ from other studies.

The emissions per litre of milk declined 9.5% in Wales from 2006 to 2015, which was more than the reduction in per litre emissions in England. Over all we saw a decline in emissions per litre of milk.

5.8. Conclusion

In this chapter, we analyse the data that would be used in this thesis. Emphasis was placed on the main inputs of dairy farming like the UAA, the number of cows, labour input and the cost of feed. We also calculated the GHG emissions from dairy farming.

Approximately, 70-73% of the total land area in the UK has been allocated for agriculture from 2006-2015. The major portion of UAA is given to cereal crops (50%) followed by temporary grass (18%) For Wales and England, 89% and 68% of the total area is the UAA. A larger portion of area in Wales has been dedicated for agriculture.

The data used for efficiency analysis has been taken from the FBS. The FBS is an annual survey that provides information on the financial, physical and economic performance of the farms. The FBS covers all types of farms but our primary focus is on the dairy farms. The data have been taken from 2006-2015. The number of dairy holdings in Wales ranges from 117 to 127 and holdings in England ranged from 301-350 over the period of 10 years. The FBS only covers a small portion of the farm in Wales and England so there is going to be some degree of sampling error. Furthermore, the number of farms vary over the years as old farms close and new farms enter.

The average farm size in the sample for Wales was 119ha in 2006 to 111ha in 2015. In England, the average farm size of sample farms was 147ha in 2006 to 151ha in 2015. On an average, the dairy farms in England are 24% larger than the dairy farms in Wales.

The average herd size on Welsh farms ranged from 115 cows to 152 cows and in England ranged from 119 cows to 152 cows from 2006-2015. The general trend is of an increase in herd size on the farms. The average farm is smaller in Wales than in England but they have relativity similar herd size with points to dairy farms in Wales being more intensive. However, the dairy cows on England farms produce more milk than the dairy cows in Welsh farms.

So, over a period of 10 years, Wales saw a 4% increase in the number of dairy cows. England saw an 8% reduction. The difference in milk production per cow between Welsh and English farms ranged from 4 to 10 hectolitres. The differences in milk production per cow can be due to differences in the feed quality and quantity, breed of the animal and its genetics.

With the increase in the number of cows per farm, the labour hours worked on the farm are also increasing. From 2006 to 2015, there was a 22% increase in the hours worked per hectare in Welsh farms and 6% increase in English farms. Majority of the work conducted on the farm is by hired labour. The hours worked on a farm by hired labour is increasing while the hours worked by farmer and his/her spouse has decreased.

Dairy farming, like other agricultural sectors is dominated by farmers aged 50 years or more. Over the course of 10 years, we saw a rise in the average age of the farmers due to an increase in the proportion of farmers belonging to the age bracket of 50-60 years. In Wales, approximately 54-64% of the farms in the sample over the years had only high school education (A-Levels or below) whereas in England 40-50% of the farms had a high school education. In both England and Wales, the level of education is rising as more and more farmers are opting for a college education as shown by the increase in the percentage of farmers having a college degrees, over the period of 10 years. Then we looked at the expenditure on animal feed per farm. With the increasing herd size, the expenditure on feed per farm has risen more than a 100% over the sample period. The increase in feed costs is not only due to the increase in the number of animals per farm. The cost of feed per animal has also rise due to an increase in the cost of feed per unit.

Lastly, we calculated the GHG emissions from dairy farming. The main emissions estimated were methane and nitrous oxides using IPCC (2006)guidelines. The emissions were then presented according to their GWP in kilograms of CO_2 equivalents. The emissions of methane were thrice as much as the emissions from nitrous oxide. In the year 2015, the total CO_2 equivalent emissions per litre of milk produced in Wales was 0.68 kgs and in England was 0.65 kgs. Over the years, we saw a decline in the emissions per litre of milk produced.

The next few chapters in this thesis will be based on the data analysed in this chapter.

5.9. Appendix

Appendix 5. 1: UK dairy data- Total number of cows and cattle and milk production in the UK from (2006-2015)

	Total Cows (000)[21]	Total cattle numbers (000)[22]	Total milk produced (hl)
2006	3,725	10,644	13,902
2007	3,647	10,370	13,619
2008	3,569	10,163	13,319
2009	3,471	10,082	13,128
2010	3,498	10,170	13,453
2011	3,482	9,988	13,665
2012	3,463	9,952	13,443
2013	3,393	9,844	13,533
2014	3,411	9,837	14,616
2015	3,472	9,919	15,005

Source: DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018e)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)DEFRA (2018d)

[21] Total cows include all the dairy and beef animal aged 2 years or older
[22] Total cattle include all the cows and beef animals in the UK

Appendix 5. 2 : The number of dairy cows and milk produced in Wales and England (2006-2015)

	Wales		England	
	Cows	Milk Produced (hl)	Cows	Milk Produced (hl)
2006	14,650	911,301	38,434	2,687,587
2007	15,625	961,132	38,390	2,657,782
2008	16,199	1,010,439	43,390	2,989,407
2009	16,628	999,618	45,967	3,224,833
2010	16,421	1,059,050	46,839	3,327,565
2011	16,747	1,130,979	46,593	3,382,221
2012	16,683	1,130,618	47,208	3,452,950
2013	15,993	1,043,566	45,409	3,222,801
2014	17,083	1,150,862	45,919	3,317,690
2015	17,838	1,245,659	45,879	3,379,176

Source: DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

Appendix 5. 3: Indirect N_2O emissions due to volatilization

a) Wales (2006-2015)

	Liquid/ Slurry (kg N_2O)	Solid Storage (kg N_2O)	Pasture/ range/ paddock (kg N_2O)	Dairy Spread (kg N_2O)	Total (kg N_2O)	Emissions per litre milk produced (kg CO_2 eq)
2006	20	4	0	0.389	25	0.010
2007	22	5	0	0.415	26	0.010
2008	22	5	0	0.424	27	0.010
2009	23	5	0	0.450	29	0.011
2010	24	5	0	0.461	29	0.011
2011	25	5	0	0.483	31	0.010
2012	24	5	0	0.460	29	0.010
2013	23	5	0	0.443	28	0.010
2014	26	5	0	0.502	32	0.011
2015	23	5	0	0.450	29	0.009

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

b) England (2006-2015)

	Liquid/ Slurry (kg N_2O)	Solid Storage (kg N_2O)	Pasture/ range/ paddock (kg N_2O)	Dairy Spread (kg N_2O)	Total (kg N_2O)	Emissions per litre milk produced (kg CO_2 eq)
2006	21	4	0	0.395	25	0.009
2007	21	4	0	0.402	26	0.009
2008	23	5	0	0.448	29	0.009
2009	25	5	0	0.490	31	0.009
2010	27	6	0	0.519	33	0.010
2011	24	5	0	0.461	29	0.008
2012	27	6	0	0.514	33	0.009
2013	26	5	0	0.500	32	0.009
2014	28	6	0	0.532	34	0.010
2015	24	5	0	0.456	29	0.008

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

Appendix 5. 4: Indirect emissions of N_2O emissions per farm and per litre milk produced due to leaching

a) Wales (2006-2015)

	Liquid/ Slurry (kg N_2O)	Solid Storage (kg N_2O)	Pasture/ range/ paddock (kg N_2O)	Dairy Spread (kg N_2O)	Total (kg N_2O)	Emissions per litre milk produced (kg CO_2 eq)
2006	1.14	0.32	0.94	0.13	2.51	0.001
2007	1.21	0.34	1.00	0.13	2.68	0.001
2008	1.24	0.35	1.02	0.14	2.74	0.001
2009	1.31	0.37	1.08	0.14	2.91	0.001
2010	1.35	0.38	1.11	0.15	2.98	0.001
2011	1.41	0.39	1.16	0.16	3.12	0.001
2012	1.35	0.38	1.11	0.15	2.98	0.001
2013	1.29	0.36	1.06	0.14	2.86	0.001
2014	1.47	0.41	1.21	0.16	3.25	0.001
2015	1.32	0.37	1.70	0.14	3.53	0.001

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

b) England (2006-2015)

	Liquid/ Slurry (kg N_2O)	Solid Storage (kg N_2O)	Pasture/ range/ paddock (kg N_2O)	Dairy Spread (kg N_2O)	Total (kg N_2O)	Emissions per litre milk produced (kg CO_2 eq)
2006	1.16	0.32	0.95	0.13	2.56	0.001
2007	1.18	0.33	0.97	0.13	2.60	0.001
2008	1.31	0.37	1.08	0.14	2.90	0.001
2009	1.43	0.40	1.18	0.16	3.17	0.001
2010	1.52	0.42	1.25	0.17	3.35	0.001
2011	1.35	0.38	1.11	0.15	2.98	0.001
2012	1.50	0.42	1.24	0.17	3.32	0.001
2013	1.46	0.41	1.20	0.16	3.23	0.001
2014	1.56	0.43	1.28	0.17	3.44	0.001
2015	1.33	0.37	1.72	0.15	3.58	0.001

Source: Own calculations based on IPCC (2006) and Brown, P. et al. (2017)

6. ASSESSING TECHNICAL AND ENVIRONMENTAL EFFICIENCY OF INTENSIVE AND LESS INTENSIVE FARMS IN THE UK

6.1. Introduction

The consumption of dairy products has expanded rapidly since it is an important source of dietary protein. According to OECD/FAO (2015), the global demand for dairy products will expand by 23% over a ten year period from 2014-2024. To satisfy the increase in demand for dairy products, the dairy sector needs to increase its production capacity. The dairy sector can increase milk production by using two approaches: either through farm expansion or farm intensification. The farm expansion requires additional lands that could be converted for dairy production whereas in farm intensification, the area of the farm remains unchanged but the use of inputs is increased.

An increase in dairy production through farm expansion is limited in the UK as 70% of the UK's total land area is already agricultural land. This study focuses on increasing dairy production through farm intensification. Generally, intensification methods are associated with increasing the number of cows per hectare on the farm coupled with an increase in the use of farm inputs such as feed and fertilisers (Stott, K. J. and Gourley, C. J. P. 2016; Chobtang, J. et al. 2017a; Salou, T. et al. 2017). However, the intensification methods have had a negative impact on biodiversity and air and water quality (Stott, K. J. and Gourley, C. J. P. 2016). Furthermore, agricultural intensification has been linked to increasing greenhouse gas (GHG) emissions (O'Brien, D. et al. 2014). Globally, milk production generates 2.7% of the total GHG emissions which are dominated by methane (CH_4), carbon dioxide (CO_2) and nitrous oxide (N_2O) emissions. In 2013, agriculture contributed 10% to CO_2 emissions, 54% to CH_4 and 79% to N_2O emissions in the EU area (EEA 2015).

In 2008, the Climate Change Act was established which aims to reduce GHG emissions in the UK by at least 80% (from 1990 baseline) by 2050. With the increasing demand for dairy products, it is becoming increasingly important to increase production. However, an increase in production would likely lead to an increase in the emissions which would contribute to climate change. Thus, it is important to reduce GHG emissions per unit of milk.

The trend of intensification can then have a significant effect on farm's efficiency and its output. So, it is important to determine if the intensification of dairy farms lead to an increase in their efficiency.

The goal of this chapter is to answer the research questions: Does the intensification of dairy farms reduce GHG emissions?; and does the intensification improve a farms efficiency? Thus, the aims of this chapter are three fold. Firstly, we want to identify the dairy farms who have intensive dairy production. Secondly, we want to assess which farm type (intensive or less intensive) would produce less GHG emission per hectolitre of milk. And thirdly is to examine if the intensification of farms can lead to an increase in its efficiency.

The data have been taken of dairy farms from the Farm Business Survey (FBS) for the years 2006 to 2015. The efficiency of the farms is assessed using Data Envelopment Analysis (DEA) method. DEA a non-parametric technique which measures relative efficiency of decision-making units (DMUs) (Zhu, J. 2009b). DEA assigns an efficiency score to each DMU, which is calculated in relation to other DMUs. This allows efficiency to be estimated through using multiple inputs to produce multiple outputs. DEA describes efficiency as increasing the output while using the minimum quantity of inputs. In this study, we have included greenhouse gas (GHG) emissions as an undesirable or a bad output of dairy production. So the efficiency in this study is evaluated using an undesirable output DEA model presented by Seiford, L. M. and Zhu, J. (2002). The efficiency of farms is described as increasing the good output of dairy farming like milk production while reducing bad output like GHG emissions while using the minimum quantity of inputs.

A Cluster Analysis has been used to form homogeneous groups of dairy farms within the UK. Through cluster analysis, farms are divided into two homogeneous groups which have similar characteristics and operations. These farms are categorised according to milk produced per hectare and dairy cow, GHG emissions per hectolitre of milk produced and by cows per hectare. Two farm clusters were formed, intensive and less intensive, based on their characteristics.

Intensive farms were smaller in area but produced more milk per hectare as they carried more dairy animals per hectare. Less intensive farms were larger in area and produced considerably less milk per hectare. The analysis finds that the intensive farms also produce less GHG emissions per hectolitre milk produced.

The technical efficiency of the dairy farms was then estimated using DEA. The undesirable output-oriented variable returns to scale (VRS) model was used to include the undesirable output of GHG emissions.

The structure of this chapter is as follows: Section 2 describes the data used for analysis in this chapter. Section 3 describes the methodology of the K-means cluster analysis used to separate farms into two clusters: intensive and less intensive farms and presents the results. The efficiency of the farms is estimated in Section 4 using DEA and the characteristics of efficient and inefficient farms are also discussed along with the efficiency of intensive and less intensive farms. Section 5 concludes the chapter.

6.2. Data

The data for dairy farms are taken from the Farm Business Survey from 2006 to 2015. The FBS is an annual survey that collects data on costs, output and investments of individual farms. It also provides information on the financial position and economic performance of selected farms.

The data has been taken of farms that have dairy herds of more than 20 dairy cows (Stokes, J. R. et al. 2007). A lower limit of 20 dairy cows per farm is set to eliminate farms that are rearing dairy animal for personal use. The dairy cows include only those animals that are of more than two years of age and have had at least one calf. The input variables used for estimating of efficiency are Utilised Agricultural Area (UAA), labour hours, number of cows, feed purchase by the farms and the other costs associated with farming. The output variables are the amount of milk produced, greenhouse gas emissions and other income generated on the farm.

The Utilised agricultural area (UAA) is given in hectares and includes the area of grass and fodder crop, as well as areas for rough grazing. The UAA excludes woodland and buildings, roads and water area not used for agricultural purposes.

The labour input is denoted in hours spent working on a farm. The hours worked includes part-time and full-time employees. Part-time workers are those who work on an average less than 30 hours per week on a farm. It also includes those employees who are unpaid like the farmer's spouse and possibly children or close family members. It excludes those workers who are below the age of 13 years. The FBS characterises work on the farm as all fieldwork, animal husbandry, maintenance work as well as administrative duties associated with the farm.

The variable of feed represents the expenditure on purchase of feed by the farm. This includes feed grown on the farm and is reported in £ value. Another variable included in our analysis is of other costs. As the name suggests, it covers all the other costs incurred on a farm that has not been taken as separate variables. Other costs include the costs for fertilisers, machinery, fuel etc. Other cost has been calculated using the formula:

$$\text{Other costs} = \text{Total cost before land- labour wages- feed} \tag{6.1}$$

The total cost before land, labour wages and the cost of feed are given in the FBS. The milk produced is the whole milk produced on the farm and is sold to the wholesaler or retailer directly. It includes milk used on the farm but excludes milk that is directly used by the calves. Milk produced is reported in hectolitres.

An environmental variable of GHG emissions is included to assess farm's environmental efficiency and are taken as a bad or an undesirable output. The GHG emissions are reported in kg CO_2 equivalent emission. It includes emissions of methane (CH_4) and nitrous oxide (N_2O) from enteric fermentation, manure management and application of manure to the soil. The GHG emissions are calculated using Intergovernmental Panel for Climate Change (IPCC) guidelines. The GHG emissions are discussed in detail in Chapter 5.6.

The last variable is of other income reported in £. This includes income from miscellaneous activities on a farm which includes income from the sales of calves and subsidies and grants. It is calculated using the formula:

$$\text{Other income} = \text{Total farm output- milk revenue} \tag{6.2}$$

The data used for the empirical analysis in this chapter includes unbalanced pooled data. The data for farms is pooled for two years. It means that two years' worth of data sets are combined into one. It allows us to increase the sample size and improves results. We get five separate datasets with the number of observations ranging from 885 to 860.

Table 6.1 provides information on the average farm characteristics from 2006 to 2014.

Table 6. 1: Characteristics of Dairy Farms 2006-2014[23]

	2006	2008	2010	2012	2014
UAA (ha)	140	142	140	140	138
Labour input (hrs)	7,041	7,337	7,319	7,419	7,565
Labour intensity (hrs/ha)	50	52	52	53	55
Feed (£)	57,620	55,563	104,398	105,582	115,318
Feed intensity (£/ha)	412	390	745	756	838
Cows (qty)	121	133	135	139	147
Stocking Intensity (Cows/ha)	0.87	0.93	0.96	1.00	1.07
Other costs (£)	109,235	86,432	162,706	156,081	169,290
Other costs per hectare (£/ha)	782	607	1,161	1,118	1,230
Milk produced (hl)	8,156	8,930	9,478	9,833	10,574
Milk produced per ha (hl/ha)	58	63	68	70	77
Other income (£)	125,966	93,521	156,779	141,598	136,608
Other income per ha (£/ha)	901	657	1,119	1,014	992
GHGE (kg CO_2 eq)	574,616	623,140	657,577	662,995	725,229
GHGE intensity (kg CO_2 eq /ha)	4,111	4,375	4,693	4,748	5,268
No. of obs	885	921	939	900	860

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The UAA is denoted in hectares. The average farm size, presented by UAA, has decreased by 1.5% from 2006 to 2014. An average farm was 140 hectares in area in 2006 and then declined to 138 hectares by 2014. The area of a farm cannot be changed in the short term. Small changes, either an increase or a reduction in size could be due to farmer allocating a small portion of land to other activities, temporarily.

The average hours worked on a farm has increased 7.5% from 2006 to 2014. The hours work on a farm per hectare has also increased 10% from 50 hours per hectares in 2006 to 55 hours per hectare in 2014. The total expenditure on the purchase of feed has increased over the years. There has been a 100% increase in the cost of feed purchased from 2006 to 2014. Due to the relatively unchanged area of the farm, the cost of feed per hectare has also increased. In 2006, a farm on an average spent £412 on feed per hectare which rose to £838 worth of feed per hectare by 2014.

An increase in the cost of feed per farm and hectare is not surprising as the number of dairy cows per hectare is also increasing. The herd size of an average farm in 2006 consisted of 121

[23] Weighted mean

dairy cows and it increased to 147 dairy cows by 2014. An increase in the number of cows and relatively stable area of the farm has led to an increase in stocking intensity. Stocking intensity represents the number of cows per hectare on a farm. In the year 2006, there were 0.87 cows per hectare which increase to 1.07 cows per hectare in 2014, showing a 24% increase in stocking intensity over a 10-year period.

With an increase in the number of dairy cows on a farm, the other costs have also increased. There has been a 55% increase in the other costs per farm and per hectare from 2006 to 2014. The other costs per hectare in 2006 was £782 which increased to £1,230 by 2014.

There has also been a 30% increase in the amount of milk produced by a farm from 2006 to 2014. Milk production has increased more on a farm than the number of cows which points to cows producing more milk. The increase in milk production per cow can be attributed to genetic selection , nutrition (VandeHaar, M. J. et al. 2016) and different breed of the animal (Stafford, K. J. and Gregory, N. G. 2008). Due to an increase in the number of cows per farm and hectare the amount of milk produced per hectare has increased 32%, from 58 hectolitres per hectare in 2006 to 77 hectolitres per hectare in 2014.

The other income generated per farm in 2006 was approximately £126,000 which increased to £136,600 by 2014. An 8% increase in the other income per farm and relatively unchanged area of the farm over the course of 10 years has led to a 10% increase in the other income generated per hectare on a farm. The other income per hectare in 2006 was £901 which increased to £992 in 2014.

An increase in the number of cows has led to the rise in the total GHG emission per farm. There was a 26% increase in the CO_2 equivalent GHG emissions over the course of 10 years. The GHGE per hectare increased over the sample period from 4,111 kg CO_2 equivalents in 2006 to 5,268 kgs CO_2 equivalent in 2014. The increase in the emissions per hectare is due to the increase in the number of dairy cows per hectare.

So, over the period of 10 years, the farm's size in terms of the area has remained unchanged however the number of dairy cows on a farm has increased 22%. An increase in herd size on a farm has led to an increase in the costs on the farm. The expenditure on the purchase of feed rose 100% whereas the other costs per farm rose 55%. The labour hours per farm and hectare has also increased, but increase in labour hours is less than 10%. With the advancement in technology and better management practices, the farms have reduced the requirement of labour.

As the number of dairy cows on the farms has increased, the farms are producing 30% more milk in 2014 compared to milk production per farm in 2006. The amount of milk produced has increased more than the number of dairy cows on the farm. It implies that the dairy cows are producing more milk in 2014 than they were in 2006. The other income generated on the farm only rose 8% from 2006 to 2014. It implies that the dairy farms are placing more of their efforts on dairy production rather than other activities which may generate additional income on the farm. The GHG emissions have risen 26% over the period of 10 years. It is expected as the number of cows are increasing on the farm.

With a large amount of data set, it is important to choose the correct data analysis tool which can summarize the data without losing important information. A variety of methods exists, however, Principal Component Analysis and Cluster Analysis are the most widely used approaches in data analysis.

Principal Component Analysis (PCA) may be used as a variable reduction method and as a means of finding patterns in the data (Brotzman, R. L. et al. 2015). PCA works in such a way that it combines input variables and drop the least important variable while retaining important pieces of information from those least important variables. So PCA changes the dimensional plane of the data by turning it into a new data set that represents the original data set while being smaller in terms of dimensionality (Interlenghi, S. F. et al. 2017). Clustering methods attempt to group observations based on some similarity measure. The goal of clustering is to discover natural groupings present in the data. Clustering methods can sort variables without requiring any prior assumption regarding the relationship amongst variables (Brotzman, R. L. et al. 2015).

The aim of this chapter is to group farms with similar characteristics so that we can identify the differences among them. PCA groups variable and not observations which defeats the purpose of using it in this study. Furthermore, one of the limitations of PCA is that the interpretation of independent variables becomes difficult as the data is transformed (Lee, S. 2010). Due to these limitations of PCA, it has not been used in this study. The next section of this chapter discusses some common clustering approaches.

6.3. Cluster Analysis

As mentioned before cluster analysis segregates observations into groups based on similarity. A variety of clustering approaches exists in the literature however there are three approaches most widely used.

One of such approaches is hierarchical clustering where a cluster tree or a dendrogram is created. A cluster tree shows the sequence of a cluster within each cluster. Hierarchical clustering has the advantage of creating a cluster without having to specify a priori. However hierarchical clustering is static in nature so the data points cannot move from one cluster to another (Omran, M. et al. 2007). Using hierarchical clustering therefore would not be suitable for this study as the variables used for cluster analysis would change on a year to year basis. Furthermore, hierarchical clustering is not suitable for large data sets which excludes us from using it in this study.

Another method of clustering is density-based clustering where the clusters are only formed of the data points tightly packed together. It assumes that data points far away are noise. As with hierarchical clustering, density-based clustering also does not require a pre-set number of clusters. However, density-based clustering fails to utilize all the data set as data points in the sparse area are not considered.

The K-means cluster analysis is another method of clustering where the observations are grouped into k clusters in which each observation belongs to the cluster with the nearest mean. K-means cluster analysis is used in this study to group the data into different clusters as this approach can deal with large data sets that the hierarchical cluster finds difficult to do. It also allows for the data points to move from one cluster to another over the years (Omran, M. et al. 2007). Furthermore, K-means cluster analysis does not disregard observations like in Density-based clustering and so no information is lost.

In this chapter, K-means cluster analysis is employed to group similar data into clusters. The K-means is an unsupervised learning algorithm where the algorithm tries to find patterns in the data rather than the researchers predicting the outcome of the analysis. In K-means cluster analysis, ‘K’ represents the number of clusters to be grouped. This allows flexibility to choose the number of clusters.

K-Means cluster analysis has been used in other studies to group dairy farms For example, Mu, W. et al. (2017) used the data from 32 specialised dairy farms in Europe to measure nitrogen use efficiency. The farms were sorted into homogeneous groups by using two-stage cluster analysis. They selected five criteria for the cluster analysis: grazing hours; soil type; concentrate per cow; milk production per cow and milk production per hectare. The two farm types were derived from the cluster. In cluster 1, the farms were located on the sandy soil and were intensive in milk production. The farms in cluster 2 were less intensive, had a higher number of grazing hours and had lower concentrate use per cow.

Cluster analysis was also used by Alvarez, A. et al. (2008) to separate dairy farms in Spain into intensive and extensive farms. The data were taken from a balanced panel of 224 dairy farms over an 8-year period, located in Northern Spain. They also evaluated the cost efficiency of extensive and intensive dairy farms using Stochastic Frontier Analysis (SFA). The result showed that the number of farms sorted into the intensive cluster were increasing. Furthermore, they found that the intensive farms produced more milk, owned more productive cows, and were smaller in size with a lower total average cost than the extensive farms.

6.3.1. Methodology

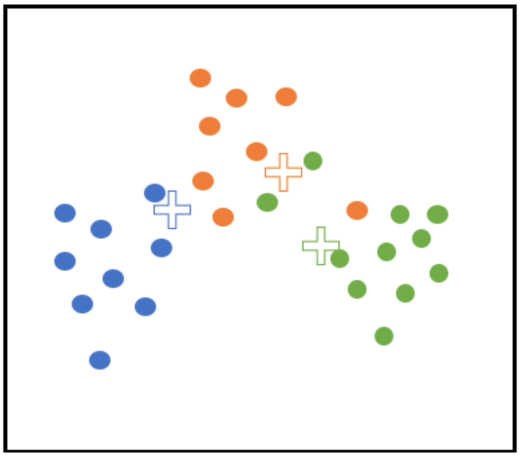
The K-means cluster analysis uses a centroid-based algorithm. A centroid is a data point around which the clusters are formed. Each data point is assigned to a centroid and several data points around a centroid form a cluster. The clusters are K in number.

The mean of these clusters is calculated which creates new centroids. The process is repeated using the new centroids to form clusters with different data points as before. The algorithm is iterated until the centroid stops moving and no data point changes the cluster. This way we can minimise the distance from every centroid to the data points in the clusters.

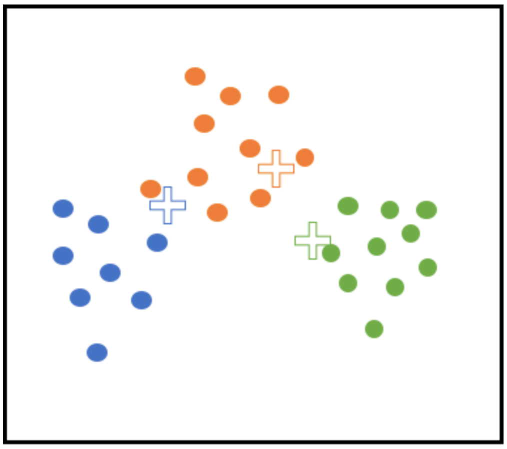
Figure 6.1 shows how the clusters are formed from three centroids. The centroids are indicated with + and all data points in the same cluster are shown with similar colours. In Figure 6.1 (a) we have the first iteration where the data points are assigned to a centroid. After that, the centroid is updated by taking the mean of the data points belonging to that cluster. In the second step, Figure 6.1 (b), the data points are assigned to the updated centroids. The mean is calculated again to update the centroids until a solution converges. Finally, in Figure 6.1 (c) clusters are formed when the centroids cease to move.

Figure 6. 1: K-means Cluster analysis algorithm to find three clusters

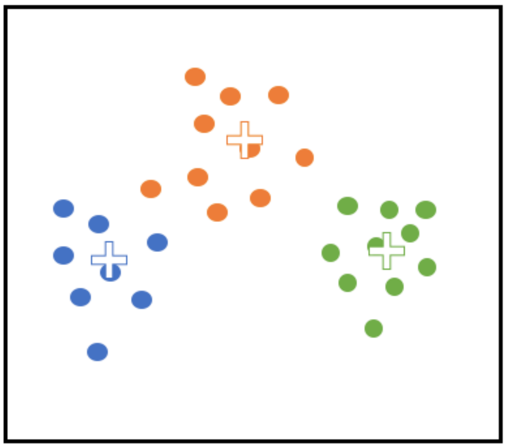
a) Iteration 1



b) Iteration 2



c) Iteration 3



For the K-means cluster analysis, the distance is measured through Euclidean means (Hartigan, J. A. and Wong, M. A. 1979). The formula to calculate the distance under the Euclidean measure between two points in a plane with coordinates *(x, y)* and *(a, b)*:

$$dist\big((x, y), (a, b)\big) = \sqrt{(x-a)^2 + (y-b)^2}$$

6.3.2. <u>Hypothesis Testing</u>

The intent of hypothesis testing is to examine whether two hypotheses are mutually exclusive or not. A test statistic is calculated according to the relevant hypothesis being tested. It is then converted to a p-value which determines if a hypothesis is rejected or not. In this study, hypothesis testing would allow for comparison and evaluation of groups of data (Helsel, D. R. and Hirsch, R. M. 2002). Hypothesis testing is being performed in this section to determine if differences exist between the two clusters (intensive and less intensive farms).

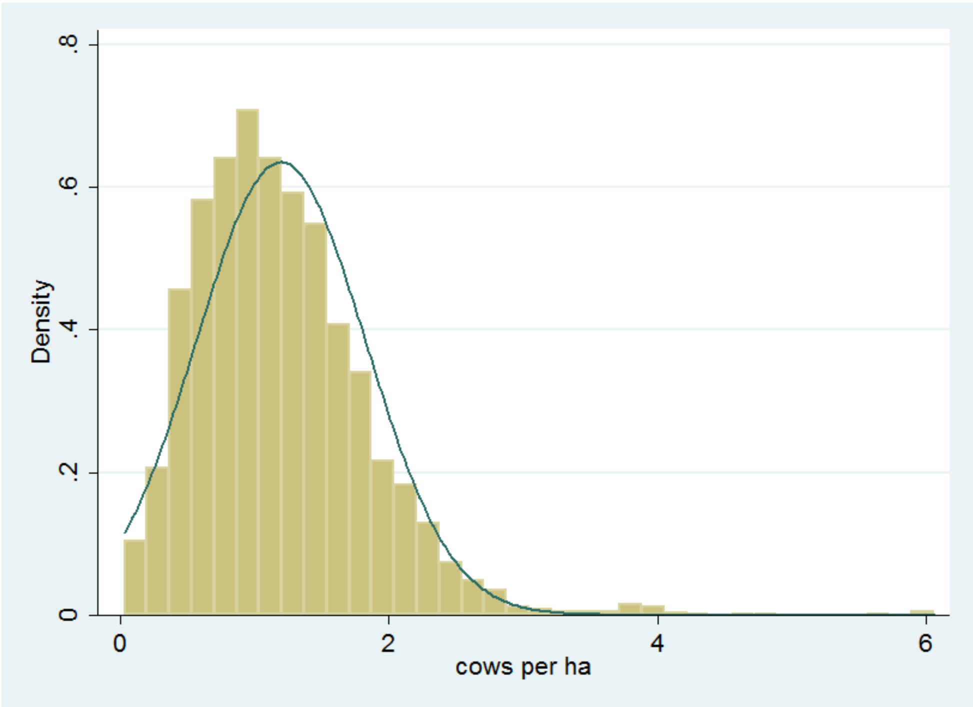
Before performing hypothesis testing, it is important to select an appropriate test to perform. Two groups of data may be compared using parametric or non-parametric tests. A parametric test assumes that the data's distribution is known (generally normal distribution). The parametric tests for hypothesis testing include student's t-test and analysis of variance (ANOVA). Hypothesis testing undertaken without assuming that data follows any distribution is known as a non-parametric test. The non-parametric tests include Kolmogorov-Smirnov test, Wilcoxon signed-rank test, Kruskal-Wallis test, and Mann-Whitney U test (Massey, A. and Miller, S. J. 2006).

Choosing an appropriate method for hypothesis testing is based on whether a distribution is known for the data. If similar data, in the past, has been normally distributed then parametric tests should be used. However, if data is expected to be non-normal or the distribution is not known then non-parametric testing is preferred (Helsel, D. R. and Hirsch, R. M. 2002).

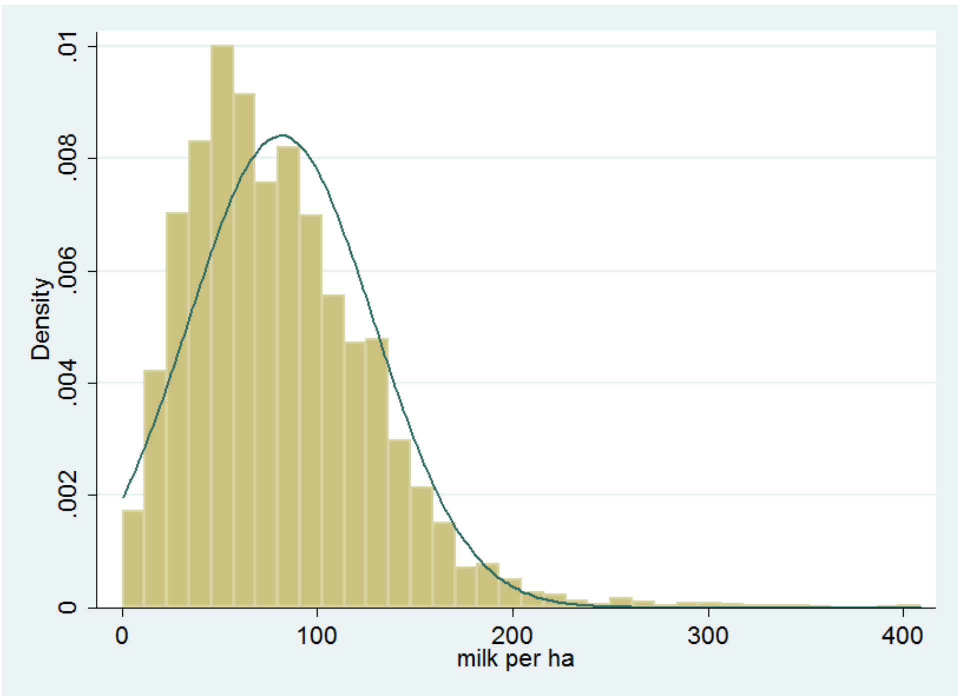
To test if the data is normally distributed, visual inspection can be undertaken through the use of histograms (Altman, D. G. and Bland, J. M. 1995). If the pattern of the frequency distribution in a histogram is bell-shaped then the data is considered as having a normal distribution. In a normal distribution, the plots are likely to occur on one side of the average as on the other side hence making the bell-shaped curve symmetrical. So to determine whether the data were normally distributed, histograms were created for the separation variables used in cluster analysis to determine their distribution. Figure 6.2 presents histogram and a normal distribution for the separation variables.

Figure 6. 2: Histograms and normal distribution for separation varaibles for all years

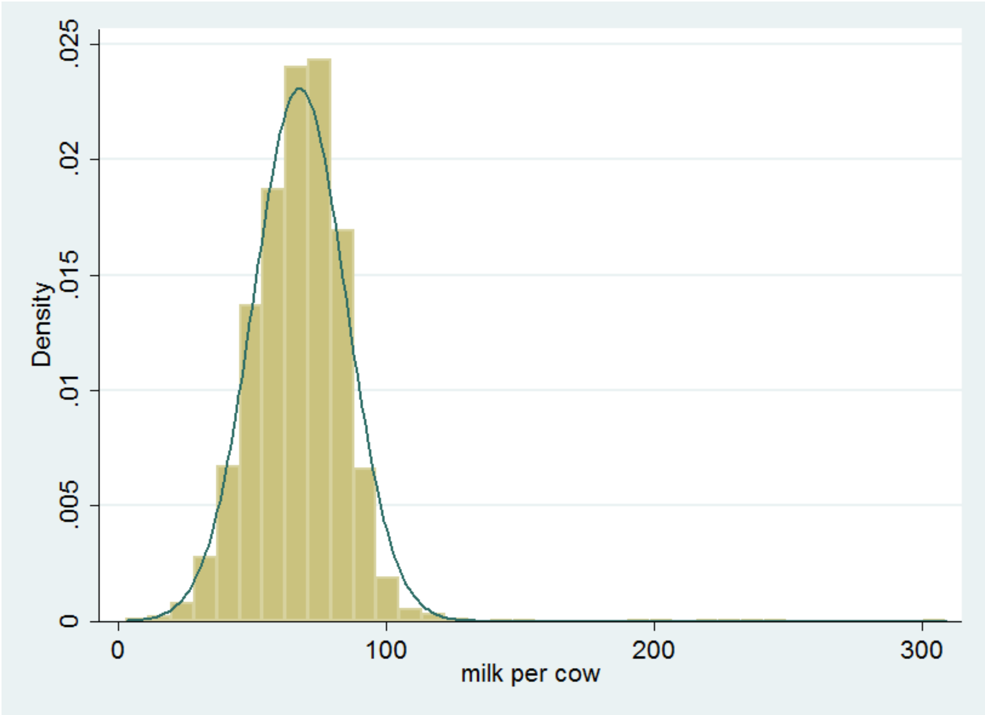
a) Cows per hectare (cows/ha)



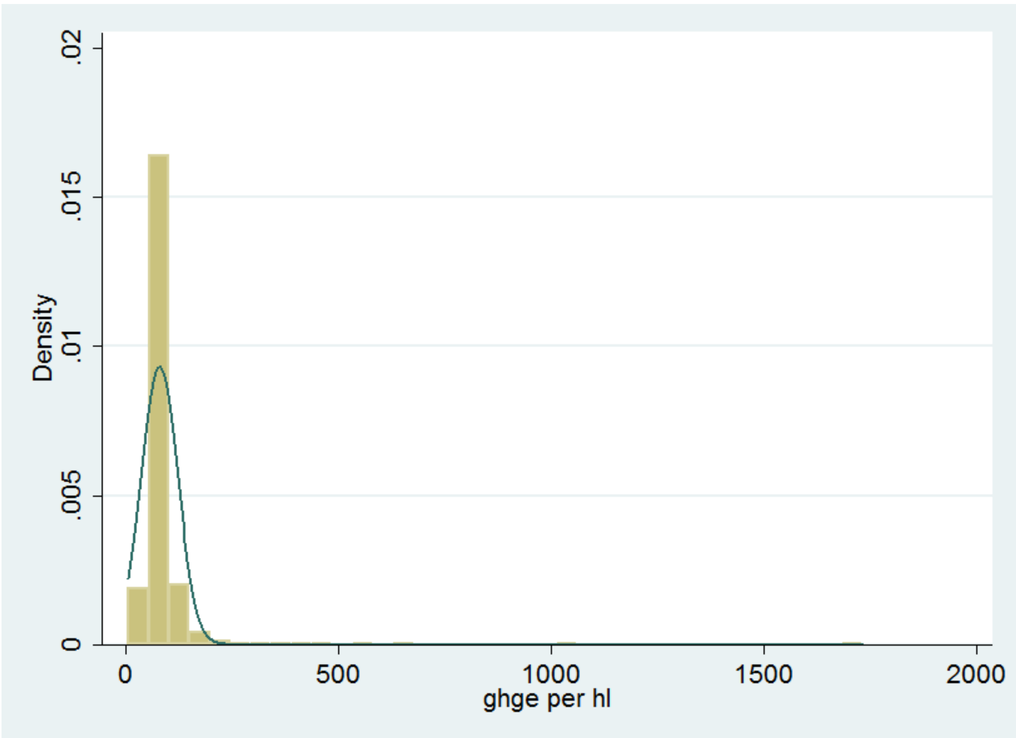
b) Milk per hectare (hl/ha)



c) milk per cow (hl/cow)



d) GHGE per hectolitre of milk (kg CO_2/hl)



Visual inspection shows that the separation variable's data has an asymmetric curve indicating it to be non-normally distributed. However, visual inspection though histograms is unreliable and does not guarantee that the distribution is normal (Ghasemi, A. and Zahediasl, S. 2012) so skewness of the distribution is quantified to solidify the case for non-normality of data. Skewness measures asymmetry in the distribution of the data. The data can either skew towards the right or left. The command in Stata 'sktest' was used to measure skewness. It tested the null hypothesis of data is normally distributed. Table 6.2 presents p-values of Skewness test for normality for the year 2006.

Table 6. 2: Skewness test for normality of separation varaibles (Year 2006)

	P- value	**Sig**
Stocking Intensity (cows/ha)	0.000	***
Milk produced per hectare (hl/ha)	0.000	***
Milk produced per cow (hl/cow)	0.000	***
GHGE per milk produced (kg CO_2 eq/hl)	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

The p-values of all the separation variables, stocking intensity, milk production per hectare and per cow and GHGE per hectoliter of milk are less than 0.05 implying that we can reject the null hypothesis of normally distributed data. This shows that the separation variables are non-normally distributed, hence non-parametric methods should be used for evaluating differences among the clusters. Skewness test was also performed for the the remaining four years and the significance values are reported in Appendix 6.1. we werer able to reject the null of normally distributed data for tall the years which implied that the serepreation variabes are non-norammly distributed and thus non-paramteric tests would be best for evatlating differences in clusters.

A variety of non-parametric methods exist like Wilcoxon signed rank test, Kolmogorov-Smirnov Test, Kruskal-Wallis Test and Mann-Whitney U test. Wilcoxon signed rank test tests the hypothesis about the location of a population distribution whereas the Kolmogorov-Smirnov test is used to test whether or not two samples come from the same distribution. Kruskal-Wallis test is an extension of the Wilcoxon tests and is used to test the null hypothesis that all populations have identical distribution functions. Mann-Whitney U test is used to test the null hypothesis that the two populations have identical distribution. The non-parametric tests, in this study, are needed to test whether significant differences exist between the two clusters and so Mann-Whitney U test is preferred.

Mann-Whitney U test

The Mann-Whitney U test was carried out to test whether the two clusters come from the same population. It is a non-parametric test, which is used in place of an unpaired t-test. It assumes that two distributions are similar in shape and that the observations in groups are independent of each other.

Suppose that we have a sample of n_x observations $\{x_1, x_2, \dots \dots x_n\}$ in one group and a sample of n_y observations $\{y_1, y_2, \dots \dots y_n\}$ in another group. The Mann –Whitney test compares every observation x_i in the sample with every observation y_j in the other sample. The total number of pairwise comparisons that can be made is $n_x n_y$.

So, if both the samples have the same median, then each of x_i would have an equal chance of being smaller or greater than each y_i. Thus, the null hypothesis would be:

$$H_0 : P(x_i > y_j) = \frac{1}{2}$$

And alternative hypothesis

$$H_1 : P(x_i > y_j) \neq \frac{1}{2}$$

We count the number of times x_i from our first sample is greater than y_j, which is denoted as U_x. We also need to count the number of times x_i in sample 1 is smaller than the y_j in their sample 2, which is denoted by U_y. Then under the null hypothesis, U_x and U_y should be equal to each other. The test is carried out by following the procedure:

1. Arrange all the observations in ascending order.
2. With every observation, mark the cluster that they belong to. Observation x_i belonged to cluster 1 and observation y_j belonged to cluster 2. n_x was the number of farms in cluster 1 and n_y , farms in cluster 2.
3. With each x write down the number of $y's$ before it, indicating $x_i > y_j$ and with each y, write down the number of $x's$ before it is indicating $x_i < y_j$

4. Adding up the total number of time $x_i > y_j$, denoted by U_x and adding the times $x_i < y_j$, denoting it as U_y.

5. Calculate $U = min\ (U_x, U_y)$

6. Using normal approximation:

$$z = \frac{U - \frac{n_x n_y}{2}}{\sqrt{\frac{n_x n_y (N+1)}{12}}} \tag{6.3}$$

The z-score provided us with the two-sided p-value.

If the p-value >0.05, the null of both the cluster representing the same population was not rejected and if p-value was <0.05, the null was rejected.

Mann-Whitney U test was carried out to test whether the sample from intensive and less intensive farms was from the same population. The test was undertaken in order to accurately differentiate between the intensive and extensive farms. We used this method to test four hypotheses.

H_0 : Milk produced per cow is the same for intensive and less intensive farms

H_0 : Milk produced per hectare is the same for intensive and less intensive farms

H_0 : Number of dairy cows per hectare are the same for intensive and less intensive farms

H_0 : GHG emissions per hectolire of milk are the same for intensive and less intensive farms

Mann-Whitney U test will also be used in other chapters to evaluate if statistically significant differences exist between the groups.

6.3.3. Characteristics of separation variables

The K-means cluster analysis allows us to hypothesise the number of clusters that the data can be sub-divided into. To classify our sample using K-means cluster analysis the separation variables included were; milk produced per hectare and per dairy cow; GHG emissions per hectolitre of milk produced and the dairy cows per hectare. The cows per hectare is also referred to as the stocking intensity.

Table 6.3 examines the characteristics of separation variables used for the cluster analysis of dairy farms.

The number of observations varies over the years and ranges from 860 farms to 921 farms. The milk production per hectare, on an average, has increased from 58 hl per hectare in 2006 to 77 hl per hectare in 2014. The milk production per dairy cow has also increased. In the year 2006, one cow produced 67 hectolitres of milk in a year on an average which increased to 72 hectolitres of milk per cow in 2014. This suggests that the dairy animals themselves are becoming more productive. An increase in milk production per cow is likely due to improvements in the composition of feed and selective breeding (Stafford, K. J. and Gregory, N. G. 2008; Hanrahan, L. et al. 2018).

Table 6. 3: Characteristics of separation variables for Cluster Analysis[24]

	No. of obs	Stocking Intensity (cows/ha)	Milk produced per ha (hl/ha)	Milk produced per cow (hl/cow)	GHGE per milk produced (kg CO_2 eq/hl)
2006	885	0.86 (0.61)	58 (45.44)	67 (17.32)	70 (29.15)
2008	921	0.94 (0.63)	63 (45.34)	67 (17.93)	70 (29.60)
2010	939	0.96 (0.64)	68 (47.41)	70 (15.93)	69 (69.26)
2012	900	0.99 (0.62)	70 (46.86)	71 (18.75)	68 (38.95)
2014	860	1.06 (0.64)	77 (51.08)	72 (16.01)	69 (30.81)

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The GHG emissions per hectolitre of milk produced have remained relatively stagnant over the course of 10 years. The emissions decreased from 70 kg CO_2 equivalent per hectolitre of milk in 2006 to 69 kg CO_2 equivalents per hectolitre of milk in 2014. The stocking intensity represents the number of cows per hectares. Stocking intensity has increased over the years. There has been a 23% increase in the number of cows per hectare from 2006 to 2014 due to which we see an increase in the amount of milk produced per hectare.

Before performing cluster analysis, it needs to be decided whether or not to standardize the data. Data standardization is a process used to scale variables of different magnitudes in the

[24] Values in brackets are the standard deviation

data set. Standardizing data can have serious effects on the clustering process by diluting the differences between the groups of variables.

The separation variables in this study have not been standardized prior to clustering. However, outliers were removed from the data set that were causing problems with the clustering process. Apart from that, three out of four of our separation variables (milk produced per hectare and per cow and GHGE per hl of milk) have similar magnitudes. Next section presents the results of cluster analysis on unstandardized data.

6.3.4. Results

As highlighted earlier, the K-means cluster analysis aims to separate farms into two groups: intensive farms and less intensive farms. The algorithm allowed us to change the classification of the farms, so numbers of intensive and less intensive farms were different every year. Two clusters were formed using the K-means cluster analysis. The number of farms separated into each cluster is presented in Table 6.4[25].

Table 6. 4: Number of farm in clusters

	Cluster 1	Cluster 2	Total
2006	540	345	885
2008	583	338	921
2010	547	392	939
2012	540	360	900
2014	546	314	860

The number of farms in Cluster 1 and Cluster 2 varies over the years. A higher percentage of farms are sorted in Cluster 1 than in Cluster 2. The number of farms in Cluster 1 ranged from 540 to 583 whereas the farms in Cluster 2 ranged from 314 farms to 392 farms. So, 58-63% of the farms were sorted into Cluster 1 and 37-42% of the farms were sorted into Cluster 2 over a 10-year period.

[25] The separation variables for the year 2006 were standardized using the simple method of subtracting the variable with its mean and dividing by the standard deviation. K means cluster analysis was performed on the standardized data. Only 1.6% (14 farms) of the farms changed clusters when using standardized data as compared to unstandardized data. Clusters changed slightly form unstandardized data to standardized data. The average and standard deviation of unstandardized and standardized data are reported in Appendix 6.2. the average and standard deviation show that formation of clusters through standardized and unstandardized data differs very slightly so not standardizing the data would not have any major impacts on the result.

To determine which cluster includes intensive or less intensive farms, we need to look at their properties. Certain assumptions were made based on the literature. The intensification of a dairy production system involves increasing milk production per hectare or per cow. Increasing milk production per hectare requires intensive use of forage and feed. It also includes having dairy animals housed for a more extended period with little or no access to pasture. Increasing size of the dairy herd would also lead to an increase in milk production per hectare (Stafford, K. J. and Gregory, N. G. 2008). Intensification through an increase in milk production per cow involves feeding animals more concentrates and maize rich diet (Styles, D. et al. 2017). Emphasis is given to intensification through an increase in milk production per hectare where there is a limited land area available.

Generally, intensive farms are smaller, but they contain more dairy cows and produce more milk. No assumptions were made about the GHG emission in intensive farms. We hoped that cluster analysis would help to identify the size of emission in both farm types

Table 6.5 provides information on the separation variables in Cluster 1 and Cluster 2.

Table 6. 5: Separation Variables in both clusters[26]

	Stocking Intensity (cows/ha)		Milk produced per hectare (hl/ha)		Milk produced per cow (hl/cow)		GHGE per milk produced (kg CO_2 eq/hl)	
	1	2	1	2	1	2	1	2
2006	0.61 (0.37)	1.57 (0.52)	38 (19.37)	115 (37.75)	62 (16.22)	73 (16.07)	79 (33.11)	63 (11.36)
2008	0.68 (0.40)	1.64 (0.57)	42 (20.78)	120 (36.05)	62 (16.79)	73 (16.67)	78 (33.71)	62 (10.27)
2010	0.67 (0.41)	1.56 (0.59)	43 (21.13)	119 (38.43)	63 (15.66)	76 (11.37)	79 (88.30)	62 (10.44)
2012	0.74 (0.44)	1.56 (0.56)	47 (22.13)	122 (39.08)	63 (15.33)	78 (18.91)	80 (44.56)	57 (15.50)
2014	0.8 (0.42)	1.73 (0.58)	52 (24.02)	136 (43.91)	65 (15.44)	79 (11.99)	77 (35.19)	61 (10.98)

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The farms in Cluster 2 have higher stocking intensity than the farms in Cluster 1. The farms in Cluster 1 contains approximately 1 cow per hectare whereas the farms in Cluster 2 contains 2 cows per hectare over the period of 10 years. Since Cluster 2 has a higher stocking intensity,

[26] Values in brackets are the standard deviation

the farms in Cluster 2 also produce more milk per hectare. A farm in Cluster 2 produces 115 hl of milk per hectare compared to only 38 hl of milk per hectare in the year 2006, on an average. The milk production per hectare is increasing for both the clusters. Over the period of 10 years, the milk production per hectare in Cluster 1 has increased 37% whereas milk production per hectare in Cluster 2 has increased by 19%.

The dairy cows in Cluster 1 produced less milk per cow than the cows in Cluster 2. The cows in Cluster 2 produced 73 to 79 hl of milk per cow whereas the cows in Cluster 1 produced 62 to 65 hl of milk from 2006 to 2014. Over the period of 10 years, the farms in Cluster 1 increased their milk production per cow by 5% whereas the farms in Cluster 2 increased their milk production per cow by 8%. So, the cows in Cluster 2 were more productive and their productivity increased more over the 10-year period than the cows in Cluster 1.

A higher stocking intensity, milk production per hectare and per cow suggested that the farms in Cluster 2 are intensive farms while the farms in Cluster 1 are less intensive farms. It satisfies the assumptions we made earlier about intensive farms. It was interesting to note that the GHG emissions per hectolitre of milk produced were less in Cluster 2 (intensive farms) as compared to Cluster 1 (less intensive farms). The farms in Cluster 1 produced 77 to 80 kg of CO_2 equivalent emissions per hectolitre of milk and the farms in Cluster 2 produced 57-63 kg CO_2 equivalent emissions per hectolitre of milk produced from 2006 to 2014.

The farms in Cluster 2 (intensive farms) have a higher potential to reduce GHG emissions. The trend over the years is the same for both the clusters with the emission decreasing approximately by 3% over the years. The improvements in nutrition and animal genetics have led to an increase in the production of milk per cow with a marginal increase in the GHG emissions (Pinares-Patiño, C. S. et al. 2009). A decline in GHG emissions per milk production through intensification has been observed by many studies including Pinares-Patiño, C. S. et al. (2009) and Bogaerts, M. et al. (2017). Intensification through an increase in quality and quantity of forage has led to a reduction in GHGE per kg carcass weight for beef animals (Cardoso, A. S. et al. 2016).

In conclusion, the farms in Cluster 2 had a higher stocking intensity so these farms also produced more milk per hectare. The dairy cows in farms in Cluster 2 also produced more milk than the cows in farms in Cluster 1. Furthermore, we found that the GHG emissions per hectolitre of milk were lower for farms in Cluster 2. These properties of Cluster 2 satisfied prior assumptions made about the intensive farms and so farms in Cluster 2 are therefore labelled as intensive farms. The farms in Cluster 1 are then labelled as less intensive farms. We find that the intensive farms produce more milk per hectare and per cow but generate less GHG emissions per output making intensive farms environmentally sustainable. The intensive farms produce more output per animal while generating less GHG emissions per output hence answering the first research question that the intensive farms do produce less GHG emissions.

The farms have now been classified into two clusters and have been labelled as intensive and less intensive farms. It is now important to evaluate the differences between intensive and less intensive farms by the variables used for estimating the efficiency of farms.

The characteristic of intensive and less intensive farms for the years 2006 and 2014[27] are presented in Table 6.6.

The UAA for the farms in Cluster 2 was 95 hectares and for the farms in Cluster 2 was 169 in the year 2006. So, the farms in Cluster 2 were 44% smaller in area than the farms in Cluster 1. Similarly, an average farm in Cluster 2 in the year 2014 was 28% smaller than the farms in Cluster 1 in the same year. However, over the period of 10 years, the average area of the farms in Cluster 2 has increased 17% whereas the average area of the farms in Cluster 1 has reduced by 9%. So, the farms in Cluster 1 are growing smaller in area whereas the farms in Cluster 2 are becoming larger in area. An increase in farms size regarding area can be expected in the farms in Cluster 2 as these farms are increasing their herd size and so would need more space to accommodate the increase in animal numbers.

The labour hours worked on Cluster 1 farms in the year 2006 was 7,119 hours compared to 6,918 hours on farms in Cluster 2 however the difference in labour hours between the two farm types was not significant. The labour hours worked on an average farm in Cluster 1 in the year 2014 was 7,128 hours and Cluster 2 was 8,325 hours. So, despite farms in Cluster 1 being larger in the area, the farmers worked fewer hours on the farm.

The differences in the feed purchased by an average farm in Cluster 1 and Cluster 2 was statistically significant for the years 2006 and 2014. In the year 2006, the farms in Cluster 1 spent £48,700 on the purchase of feed and the farms in Cluster 2 spend £71,500 on the purchase

[27] Characteristics of the intensive and less intensive farms for the years 2008, 2010 and 2012 are given in the Appendix 6.3.

of feed. So, on an average, the farms in Cluster 2 purchased 47% more feed than the farms in Cluster 1. Similarly, in the year 2014, the less intensive farms purchased less feed per farm than the farms in Cluster 2. On an average, the farms in Cluster 2 spent 77% more money on the purchase of feed than the farms in Cluster 1 in 2014. The cost of feed increased 84% in the farms in Cluster 1 compared to a 123% increase in the cost of feed in the farms in Cluster 2 over the period of 10 years

Table 6. 6: Characteristics of intensive and less intensive farms for years 2006 and 2014

	2006				2014			
	Cluster 1 (Less Intensive Farms)	Cluster 2 (Intensive Farms)			Cluster 1 (Less Intensive Farms)	Cluster 2 (Intensive Farms)		
	Mean	Mean	P-value	Sig	Mean	Mean	P-value	Sig
UAA (ha)	169	95	0.000	***	153	111	0.000	***
Labour input (hrs)	7,119	6,918	0.952		7,128	8,325	0.000	***
Feed (£)	48,701	71,580	0.000	***	89,824	15,9648	0.000	***
Cows (No.)	103	149	0.000	***	122	191	0.000	***
Other costs (£)	111,182	106,188	0.036	**	154,300	19,5355	0.000	***
Milk produced (hl)	6,434	10,851	0.000	***	7,984	15,077	0.000	***
GHG emissions (kg CO_2 eq)	505,233	683,217	0.000	***	612,141	921,873	0.000	***
Other income (£)	152,262	84,807	0.000	***	154,230	105,966	0.001	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The herd size on farms in Cluster 2 also larger for both the years. An average farm in Cluster 2 in the year 2006 contained 149 dairy cows whereas an average farm in Cluster 2 had a herd size of 103 cows. In the year 2014, the herd size of the farms in Cluster 2 increased to 191 dairy cows and the herd size of the farms in Cluster 1 increased to 122 dairy cows. An 18% and 28% increase in the herd size of the farms in Cluster 1 and Cluster 2 was observed over the period of 10 years, respectively.

The farms in Cluster 2 are becoming larger in terms of herd size due to which the labour hours and the cost of feed purchased per farm have risen. In the year 2006, other costs were 5% lower for farms in Cluster 2 however in the year 2014, other costs for Cluster 2 were 27% higher than the other costs for cluster 1. The difference between Cluster 1 and Cluster 2 for other costs was statistically significant for both the years. Analysing the other costs for the rest of the years (2008, 2010, 2012), we find that other costs are higher for farms in Cluster 2 compared to farms in Cluster 1. The lower other costs in the year 2006 for farms in Cluster 2 is due to the way the data has been presented. We need to remember that the values given in Table 6.6 are of an average farm so if we look at the other costs of individual farms then there would be farms in Cluster 2 whose other costs are higher.

The average milk production per farm in the year 2006 for farms in Cluster 1 was 6,400 hl of milk and the farms in Cluster 2 produced 10,800 hl of milk. The farms in Cluster 2 produce 69% more milk than the farms in Cluster 1. The farms in Cluster 2 are intensive farms, so they have a higher number of cows on the farms and their cows produce more milk than the cows present in farms in Cluster 1. So, it is not surprising to see that farms in Cluster 2 produce significantly higher milk. Similarly, in the year 2014, milk produced by the farms in Cluster 2 is higher than the milk produced by farms in Cluster 1. With the increase in the number of cows on the farms over the period of 10 years, we also see an increase in milk production per farm in both the Clusters. Over the period of 10 years, the farms in Cluster 1 increased their milk production by 24% whereas the farms in Cluster 2 increased their milk production per farm by 39%. A higher percentage increase in the amount of milk produced per farm from 2006 to 2014 in Cluster 2 is due to an 8% increase in milk production per cow in the farms in Cluster 2.

The GHG emissions per farm for the year 2006 and 2014 were higher for farms in Cluster 2 compared with the farms in Cluster 1. This is expected as the number of cows is higher in the farms in Cluster 2. The farms in Cluster 2 produced 35% more GHG emissions per farm than the farms in Cluster 1 in the year 2006. Compared to that, the farms in Cluster 2 purchased

51% more GHG emissions per farms than the farms in Cluster 1 in the year 2014. Thus from 2006 to 2014, the GHG emission per farm has increased 21% and 35% for farms in Cluster 1 and Cluster 2, respectively. The total GHG emissions per farm are higher for the farms in Cluster 2. However, the GHG emissions per hectolitre of milk produced are lower for farms in Cluster 2. A higher GHG emissions per farm is due to the higher number of cows in farms in Cluster 2.

Lastly, the other income generated by farms in Cluster 1 is higher than the other income generated on the farms in Cluster 2, in the years 2006 and 2014. The farms in Cluster 2 generated 44% and 31% less other income than farms in Cluster 1, in the years 2006 and 2014, respectively. Although the farms in both the clusters are dairy farms, the farms in Cluster 2 have an intensive dairy production system so their primary focus is dairy production. The farms in Cluster 1, are less intensive and their higher other income suggests that they indulge in other activities that generate more income from those activities compared to farm in Cluster 2.

Using K-means cluster analysis, farms in the data were grouped into two clusters. The farms in Cluster 1 are labelled as less intensive farms and the farms in Cluster 2 are labelled as intensive farms. The less intensive farms had lower stocking intensity, produced less milk per hectare and per cow and produce more GHG emissions per hl of milk as compared to the intensive farms. Using Mann-Whitney U test, we tested whether the differences between intensive and less intensive farms existed in the variables other than the separation variables used to define clusters. We can conclude that the clusters are homogeneous in nature as other farm variables are also statistically different in both the clusters thus validating it further that the homogeneity of clusters. [28]

The intensive farms were smaller in area than the less intensive farms and they also had a much larger herd size. Due to the higher number of dairy cows on the farms, the intensive farms used more labour, purchased more feed and had higher other costs. The intensive farms then also produced more milk per farm and more GHG emissions per farm than the less intensive farms.

[28] The standard deviation of separation variables is reported in Table 6.3 and the standard deviation of separation variables after clustering is reported in Table 6.5. A comparison of standard deviation can indicate the homogeneity of the clusters. The standard deviation of separation variables is greater than the standard deviation of separation variable for individual clusters implying that the dispersion of data set decreases when clusters are formed hence implying homogeneity of clusters. However, the standard deviation is not the only method to show that clusters are homogeneous in nature. Box and whiskers plot are used to visually show the homogeneous nature of clusters. Box and whiskers plots for separation variables are given in Appendix 6.4.

However, the less intensive farms generated higher other income as they had more diversified activities than the intensive farms.

The average farm size of intensive farms is increasing whereas it is decreasing for the less intensive farms. There is a 17% increase in the size of an intensive farm while a 9% decrease in the size of less intensive farms. The average farm's size has remained relatively unchanged over the period of 10 years with an average farm being 140 hectares in 2006 and decreasing to 138 hectares by 2014. It suggests that the total area for the dairy farm activities has not changed. It points towards consolidation of farms together with the decreasing numbers of farms. The herd size has increased over the period of 10 years for both intensive and less intensive farms and so has labour hours, cost of feed and other costs. With an increase in the number of cows in the intensive and less intensive farms from 2006 to 2014, the milk production per farm and GHG emissions per farm has also increased.

One of the main criticism of the intensive dairy production systems is the increase in the GHG emissions. An intensive dairy production would have more dairy cows on the farms so they would produce higher GHG emission per farm. However, if we look at the emissions per milk produced on the farm, we find that the intensive dairy production systems produced 20-29% less GHG emission per hectolitre of milk produced from 2006 to 2014.

Using cluster analysis, we separated farms in the sample into two clusters. The farms in both the clusters had different characteristics and labelled then as intensive farms and less intensive farms based on those characteristics. The intensive dairy farms produced higher output while using more inputs. The intensive farms were also environmentally friendly as they produce less GHG emission per hectolitre of milk produced.

However, it is important to assess the efficiency of these farms to determine which of the farms are using their inputs in the optimal combination to produce maximum output. In the next section, the method of Data Envelopment Analysis (DEA) is used to assess the efficiency of the farms. It will enable us to determine if the farms in Cluster 2 (intensive farms) are more efficient than the farms in Cluster 1 (less intensive farms).

6.4. Estimating efficiency

The cluster analysis, performed in the previous section, has helped us to identify homogeneous groups of dairy farms based on their characteristics. DEA was used to estimate the efficiency of these clusters. DEA can be either input-oriented or output-oriented. In input-oriented DEA, inputs are reduced while keeping the outputs constant to create an efficient production frontier. The output-oriented DEA, the inputs remain constant, and the production of output is increased. We have used the output-oriented DEA model where the farms maximise their output production while using the same level of inputs.

The inputs used are UAA, labour hours, feed, the number of cows and other costs that are associated with the dairy production unit. The outputs include milk produced, other income generated on the farm and GHG emissions.

6.4.1. <u>Methodology: Dealing with undesirable outputs</u>

DEA has been discussed in detail in Chapter 4. DEA evaluates the way in which a firm or a DMU might produce outputs while keeping inputs as constant. This is an output-oriented model in DEA. We would be using a variable return to scale (VRS) model also known as the Banker, Charnes and Cooper (BCC) model so the farms are benchmarked against the farms of similar size. Due to the structure of production, an increase in inputs does not result in a proportional increase in the outputs.

The DEA data domain is expressed as:

$$\begin{bmatrix} Y \\ -X \end{bmatrix} = \begin{bmatrix} Y^g \\ Y^b \\ -X \end{bmatrix} \tag{6.4}$$

Where Y^g and Y^b are desirable (Firbank, L. G. et al.) and undesirable (bad) outputs, respectively and X is the inputs. We need to increase Y^g and decrease Y^b to improve efficiency. However, in the standard BCC model, both Y^g and Y^b are increased. So, to increase the good outputs and reduce the bad outputs, we need to modify the standard BCC model.

Based on Seiford, L. M. and Zhu, J. (2002), the undesirable output of GHG emissions are transformed by multiplying the output with "-1" and then finding a proper translation vector, *w*. This translation vector *w*, converts all the negative undesirable output to positive. So, the DEA data domain changes to:

$$\begin{bmatrix} Y \\ -X \end{bmatrix} = \begin{bmatrix} Y^g \\ \bar{Y}^b \\ -X \end{bmatrix} \tag{6.5}$$

Where the j^{th} column of the translated undesirable output becomes:

$$\bar{y}_j^b = -y_j^b + w > 0 \tag{6.6}$$

So, we have a linear program:

$$\left.\begin{aligned} & max_{\phi,\lambda} \qquad h, \\ \text{St:} \quad & \textstyle\sum_{j=1}^{n} \lambda_j \, y_j^g \geq h y_0^g \\ & \textstyle\sum_{j=1}^{n} \lambda_j \, \bar{y}_j^b \geq h \bar{y}_0^b \\ & \textstyle\sum_{j=1}^{n} \lambda_j \, x_j \leq x_0 \\ & \textstyle\sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j \geq 0, \end{aligned}\right\} \tag{6.7}$$

We can also treat the undesirable output as an input but then it would not reflect the true production process (Seiford, L. M. and Zhu, J. 2002; Zhu, J. 2009b). The technical efficiency of the farms in the sample is measured for all five years, separately. The technical efficiency score in an output-oriented model has a value equal to or greater than 1. A value of 1 indicates that a farm is on the frontier and is technically efficient. The score of greater than 1 suggests that the farm is not technically efficient and it can potentially increase the outputs produced while keeping the level of inputs as constant. For example, a DMU has an efficiency score of 1.06. The DMU is technically inefficient. For the DMU to become efficient, its output production could be increased by 6% while using the same level of inputs.

The software used in this study for DEA is ‘DEA Frontier”, which is an Add-In for Microsoft Excel, developed by Professor Zhu, J. (2003). The software is based on years of Professor Zhu’s research in DEA and productivity analysis. DEA Frontier was created by Zhu, J. (2003) in an effort to reduce mistakes and misrepresentation during coding of DEA models.

6.4.2. Results

The average technical efficiency score of dairy farms is presented in Table 6.7 along with the number of technically efficient farms.

Table 6. 7: Average technical efficiency score and the number of technically efficient farms for the year 2006 to 2014

	Average efficiency	**Number of technically efficient farms**
2006	1.057	120
2008	1.056	149
2010	1.042	135
2012	1.080	118
2014	1.050	121

In the year 2006, the average technical efficiency score of dairy farms was 1.057 and the number of technically efficient farms were 120. So approximately 14% of the farms in 2006 were technically efficient and were using inputs in an optimal combination that maximised the output production while minimising the GHG emissions. The remaining 86% of the farms could potentially increase their output production by 5.7% using the same amount of inputs.

In the year 2008, 149 farms out of 921 were technically efficient and the average efficiency score for the year was 1.056. So, an average farm could potentially increase its output production by 5.6% using the same quantities of inputs. In the years 2010, 2012 and 2014 the number of technically efficient farms was 135, 118 and 121 respectively. The average efficiency score for the years 2010 and 2012 was 1.042, 1.08 and 1.05, respectively.

An average farm in the year 2010 could potentially increase its output production by 4.2% while a farm in 2012 could potentially increase its output production by 8%. Similarly, in the years 2014 and average farm could potentially increase its output production by 5%.

After evaluating the technical efficiency and the number of efficient farms, it is important to understand the differences among the technically efficient and inefficient farms.

The characteristics of technically efficient and inefficient farms for the years 2006 and 2014 are presented in Table 6.8.

Table 6. 8: Characteristics of technically efficient and inefficient farms (2006 and 2014)[29]

	2006				2014			
	TE > 1	TE = 1			TE > 1	TE = 1		
	Mean	Mean	P-value	Sig	Mean	Mean	P-value	Sig
UAA (ha)	138	148	0.007	***	135	152	0.132	
Labour input (hrs)	6,998	7,314	0.052	*	7,467	8,168	0.391	
Feed (£)	56,872	62,387	0.034	**	113,018	129,361	0.314	
Cows (No.)	118	139	0.153		143	177	0.948	
Other costs (£)	105,686	131,860	0.384		159,568	228,666	0.781	
Milk produced (hl)	7,873	9,957	0.819		10,151	13,154	0.612	
GHGE (kg CO_2 eq)	561,543	657,959	0.159		704,146	853,993	0.785	
Other income (£)	120,445	161,163	0.498		123,376	217,422	0.176	
Stocking Intensity (cows/ha)	0.85	0.94	0.031	**	1.05	1.16	0.001	***
Milk produced per ha (hl/ha)	57	67	0.026	**	75	87	0.001	***
Milk produced per cow (hl/cow)	66	71	0.374		71	74	0.171	
GHGE per milk produced (kg CO_2 eq/hl)	71	66	0.275		69	65	0.055	*
No of obs	765	120			739	121		

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

[29] Characteristics of the technically efficient and inefficient farms for the years 2008, 2010 and 2012 are given in the Appendix 6.2.

The differences between the technically efficient and inefficient farms are evaluated using the Mann-Whitney U test. The differences between technically efficient and inefficient farms were not statistically significant for input variables: number of cows and other costs for the year 2006 and 2014. Similarly, the differences between technically efficient and inefficient farms for output variables: Milk produced; GHG emissions and other income were not statistically significant implying that both farm types produced similar quantities of outputs.

In the year 2006, the area of the technically efficient farms was 148 hectares whereas the area of inefficient farms was 138 hectares. The difference in UAA between the two farm types was significant. So, the technically efficient farms were 7% larger than the inefficient farms. However, the differences in the UAA for the year 2014 was not statistically significant even though the technically efficient farm was larger in area than the inefficient farms.

The labour hours in the year 2006 was higher for the technically efficient farms. On an average, the technically efficient farms used 7,314 hours of labour per farm which was 4% higher than the labour hours used in the inefficient farms. The differences in labour hours for technically efficient and inefficient farms was statistically significant for the year 2006 but not significant for the year 2014.

The cost of feed purchased by a technically efficient farm was 10% higher than the inefficient farms in the year 2006 and the differences among the two farm types were statistically significant. Like the other inputs, the differences in the cost of feed for efficient and inefficient farms in the year 2014 was not statistically significant.

The other inputs, the number of cows and other costs were higher for the technically efficient farms in the year 2006 and 2014, but the differences were not statistically significant. It implied that both farm types contained a similar number of cows and incurred similar other costs for the year 2006 and 2014. The output variables like milk produced, GHG emission and other income per farm were all higher for technically efficient farms for both the years but the differences were not statistically significant.

However, the differences in variables that defined clusters in the previous section like stocking intensity and milk produced per hectare were statistically significant for technically efficient and inefficient farms for both the years. The stocking intensity represents the number of cows per hectare of land. The stocking intensity for technically efficient farms in the year 2006 was 0.94 cows compared to 0.85 cows in the technically inefficient farms. In the year 2014, the stocking intensity of the technically efficient and inefficient farms rose. The stocking intensity of technically efficient farm was equal to 1.16 cows and for inefficient farms was 1.05 cows.

Since the number of cows per hectare was higher for the technically efficient farms, the milk produced per hectare was also higher for technically efficient farms. In the year 2006, the technically efficient farms produced 67 hectolitres of milk whereas the inefficient farms produced 57 hectolitres of milk per hectare. In the year 2014, the technically efficient farms produced 87 hectolitres of milk per hectare compared to the inefficient farms which produced 75 hectolitres of milk per hectare.

The difference in milk production per cow was not statistically significant for technically efficient and inefficient farms in both the years implying that the cows produced similar quantities of milk on both the farms.

The GHG emissions per hectolitre of milk produced were lower for technically efficient farms but the difference was not statistically significant for the year 2006. The differences in GHG emissions per hectolitre of milk production was lower for technically efficient farms in the year 2014 and the difference was statistically significant. The efficient farm produced 65 kg of CO_2 per hectolitre of milk produced whereas the technically inefficient farms produced 69 kg of CO_2 per hectolitre of milk produced. So, the efficient farms in the year 2014 produced 6% less GHG emission per hectolitre of milk.

6.4.3. Technical efficiency of intensive and less intensive farms

The average technical efficiency scores of intensive and less intensive dairy farms is presented in Table 6.9.

Table 6. 9: Technical Efficiency score for intensive and less intensive farms (2006-2015)

	Intensive farms		Less Intensive farms			
	Technical Efficiency	Number of technically efficient farms	Technical Efficiency	Number of technically efficient farms	P-Value	Sig
2006	1.050	61	1.061	59	0.000	***
2008	1.046	82	1.062	67	0.000	***
2010	1.038	78	1.044	57	0.005	***
2012	1.073	57	1.084	61	0.160	
2014	1.042	61	1.048	60	0.018	**

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

The average technical efficiency score over the 10-year period ranged from 1.042 to 1.08 implying that the farms could on an average increase their output production by 4.2 – 8.0 % while using the same quantities on inputs. In the year 2006, the average efficiency score for intensive farms was 1.05 while the average efficiency score for less intensive farms was 1.061. So, the less intensive farms had a higher average efficiency score which indicated that they could potentially increase their output production by 6.1% while using the same quantities of inputs. Approximately 18% of the farms that were intensive were technically efficient whereas only 11% of the less intensive farms were technically efficient. So, the larger percentage of intensive farms were technically efficient and their inefficient farms could increase their output producing by only 5% while using the same quantities of inputs. The differences in the average efficiency score between the intensive and less intensive farms were statistically significant.

In the year 2008, 82 intensive farms out of 338 intensive farms were efficient whereas 67 farms out of 583 less intensive farms were technically efficient. The average efficiency score was higher for less intensive farms implying they could increase their output production by a much higher percentage than the intensive farms. The intensive farms could potentially increase their output production by 4.6%, and the less intensive farms could increase their output production by 6.2% while using the same level of inputs, and the differences were statistically significant.

The average efficiency score for intensive farms for 2010, 2012 and 2104 was lower than the average efficiency score for less intensive farms. Like the previous year, a higher percentage of intensive farms were technically efficient compared to less intensive farms. In the year 2010, 20% of the intensive farms were technically efficient and farms on an average could increase their output production by 3.8%. The less intensive farms could increase their output production by 4.4% and the differences in average efficiency score between the two groups was statistically significant. In the year 2012, the average efficiency score for the less intensive farms was lower than the average efficiency score for less intensive farms but the differences between the two groups were not statistically significant.

In the year 2014, the average efficiency score for the intensive farms was 4.2% implying that these farms could potentially increase their output production by 4.2% while using the same level of inputs. Approximately 19% of the intensive farms were technically efficient. The less intensive farms had an average efficiency score of 1.048 and only 11% of the less intensive farms were technically efficient.

Over the period of 10 years, approximately the 16 - 24% of the intensive farms were technically efficient whereas 10-11% of the less intensive farms were technically efficient. On an average, the intensive farms could increase their output production by 3.8 - 7.3% while the less intensive farms could potentially increase their output production by 4.4 - 8.4% using the same quantities of inputs. Thus, the intensive farms were more technically efficient using the right combination of inputs to produce maximum output while minimising the GHG emissions.

6.4.4. Optimal Output

Benchmarking is a good way to determine which efficient farms the inefficient farms need to mimic to become efficient. The DEA Frontier provides the farms that benchmarks or the peers of the inefficient farms. These benchmarks can help us determine changes that need to be made to the inefficient farms for them to become efficient. An inefficient farm can have more than one peer.

The DEA Frontier gives the percentage by which the inefficient farms need to mimic the efficient farm. Based on those peers and percentages, we can calculate the optimal output that could potentially be achieved by the inefficient farms using the same level of inputs. The percentage increase in the outputs (milk produced and other income) and percentage decrease in GHGs achieved by mimicking benchmarks is presented in Table 6.10.

Table 6. 10: Percentage change in the outputs

	Milk produced	GHG Emission	Other Income
2006	6%	27%	12%
2008	6%	24%	9%
2010	4%	18%	6%
2012	8%	35%	9%
2014	5%	23%	8%

In the year 2006, the average efficiency score was 1.057 which implies that the farms could on an average increase in their output production by 5.7% while using the same level of inputs. If the inefficient farms follow the production and management systems of the technically efficient farms, then they can increase their milk production by 6% and other income by 12% while reducing their GHG emissions by 27%. The percentage increase in outputs that is achieved if mimicking efficient farms is greater than the average efficiency score which denotes the percentage increase in outputs. The reason behind this is the presence of output slacks due to which the percentage increase in outputs differs, especially regarding other income.

In the year 2008, the average efficiency score was 1.056 implying that the farms could increase their output production by 5.6%. However, if the farms mimic the efficienct farms, then they can increase their milk production by 6% and increase other income by 9%. These farms can also reduce GHG emissions by 24%.

Similarly, in the years 2010, 2012 and 2014, the farms could on an average increase milk production by 4%, 8% and 5%, respectively while they can increase other income generated on the farm by 6%, 9% and 8%. If the inefficient farms follow the system of their peers, who are an efficient farm, then on an average the GHG emissions could potentially be reduced 18%, 35% and 23% in the years 2010, 2012 and 2014.

6.5. Discussion and Conclusion

Intensification is generally seen as a bad thing as it is associated with pollution, lack of biodiversity and eutrophication. However, this study shows that the intensive farms produce less emission per hectolitre of milk compared to the less intensive farms answering the first research question. Intensive farms are characterised as having higher stocking intensity, higher milk production per hectare and per cow. These results are supported by Stott, K. J. and Gourley, C. J. P. (2016) who found that the increase in milk production per hectare would improve a farms' Nitrogen use efficiency thereby reducing the emission. Bell, M. J. et al. (2011) found that the CO_2 equivalent emissions per kilogram of energy corrected milk and per hectare could be reduced by increasing milk production per hectare if combined with improvements in feed utilisation. Furthermore, we found that the intensive farms are more technically efficient than the less intensive farms.

Using K-means cluster analysis, the dairy farms over the period of 10 years (2006 to 2014) were separated into two clusters; intensive farms and less intensive farm. The number of farms in years ranged from 860 to 939 farms. It was found that 37-42% of the farms were intensive farms whereas 58-63% of the farms were less intensive farms. As the literature suggests, intensive farms produced more milk per hectare and per cow. These farms also had a higher stocking intensity (cows per hectare). Furthermore, the GHG emissions per hectolitre of milk produced were lower for intensive farms. The intensive farms produced 57-63 kg of CO_2 equivalent emissions over the period of 10 years. The GHG emissions from intensive farms were found to be 20-29% lower than the emissions from the less intensive farms. This answer the first research question that the intensive farms do produce less GHG emissions per hectolitre of milk produced by the farm.

Some studies like Dantsis, T. et al. (2010) and Llanos, E. et al. (2018) have found that intensification negatively affects the environment as they assume that the intensification of the production system is through the increase in fertiliser use. Although the quantity of fertiliser used by the dairy farm has not been evaluated directly in this study, the effect of fertiliser has been included in the calculations of the GHG emissions in Chapter 5.6.

The intensive farms were also smaller in area and had higher costs and input use due to larger herd size. However, the less intensive farms generated higher other income from the farms which implied that the less intensive farms had diversified their income sources.

The efficiency of the dairy farms was estimated using undesirable DEA model presented by Seiford, L. M. and Zhu, J. (2002). The three outputs taken for dairy farms were the milk production in hectolitres, other income generated on the farm in £ value and the GHG emissions denoted in kilograms CO_2 equivalent emissions. The undesirable DEA model was an output-oriented model in which the farm's efficiency is determined by maximising the production of its outputs while keeping the level of input quantities as the same. It allowed us to estimate the technical efficiency of the farms by maximising desirable or good outputs like milk production and other income and by reducing the undesirable or bad outputs like GHG emissions, simultaneously. Approximately 13-16% of the farms were technically efficient implying that they were producing maximum outputs (milk and other income) and reducing undesirable output (GHG emissions) while using the optimal combination of inputs. These farms then could increase their output production by 4.2-8% while using the same level of inputs. A higher percentage of intensive farms were technically efficient compared to the less intensive farms. Approximately 16-24% of the intensive farms in the sample were technically efficient whereas 10-11% of the less intensive farms were technically efficient.

Furthermore, the intensive farms had lower average efficiency score than the less intensive farms. So, the intensive farms could potentially increase their output production by less percentage while using the same quantities of inputs. Thus, the intensive farms were more technically efficient than the less intensive farms answering the second research question about which type of farm may exhibit higher efficiency. If the inefficient farms followed the production system of the efficient farms then the inefficient farms could potentially decrease, on an average, farm's total GHG emissions by 18-35%.

6.6. Appendix

Appendix 6. 1: Skewness test for normality of separation varaibles

a) 2008

	P-Value	Sig
Stocking Intensity (cows/ha)	0.000	***
Milk produced per hectare (hl/ha)	0.000	***
Milk produced per cow (hl/cow)	0.000	***
GHGE per milk produced (kg CO_2 eq/hl)	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

b) 2010

	P-Value	Sig
Stocking Intensity (cows/ha)	0.000	***
Milk produced per hectare (hl/ha)	0.000	***
Milk produced per cow (hl/cow)	0.000	***
GHGE per milk produced (kg CO_2 eq/hl)	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

c) 2012

	P-Value	Sig
Stocking Intensity (cows/ha)	0.000	***
Milk produced per hectare (hl/ha)	0.000	***
Milk produced per cow (hl/cow)	0.000	***
GHGE per milk produced (kg CO_2 eq/hl)	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

d) 2014

	P-Value	Sig
Stocking Intensity (cows/ha)	0.000	***
Milk produced per hectare (hl/ha)	0.000	***
Milk produced per cow (hl/cow)	0.001	***
GHGE per milk produced (kg CO_2 eq/hl)	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

Appendix 6. 2: Average and standard deviation of separation variables unstandardized and standardized data according to clusters (Year=2006)[1,2]

Clusters[3]	Stocking Intensity (cows/ha)		Milk produced per hectare (hl/ha)		Milk produced per cow (hl/cow)		GHGE per milk produced (kg CO_2 eq/hl)	
	USD	SD	USD	SD	USD	SD	USD	SD
1	0.78 (0.37)	0.79 (0.37)	45.35 (19.37)	45.35 (19.37)	60.12 (16.22)	60.66 (14.98)	88.80 (33.11)	88.19 (33.23)
2	1.64 (0.52)	1.67 (0.53)	117.73 (37.75)	117.73 (37.75)	73.77 (16.07)	73.48 (17.36)	64.74 (11.36)	64.72 (11.58)

Note: [1] values in brackets are the standard deviation.
[2] USD: unstandardized data, SD: standardized data.
[3] cluster 1 is less intensive farms and cluster 2 is less intensive farms.

Appendix 6. 3: Average characteristics of intensive and less intensive (2008, 2010 and 2012)[30]

a) 2008

	Cluster 1 (Less Intensive Farms)	Cluster 2 (Intensive Farms)	P-value	Sig
	Mean	Mean		
UAA (ha)	166	103	0.000	***
Labour input (hrs)	7,216	7,545	0.024	**
Feed (£)	45,967	72,115	0.000	***
Cows (No.)	112	168	0.000	***
Other costs (£)	83,227	91,960	0.002	***
Milk produced (hl)	6,971	12,309	0.000	***
GHG emissions (kg CO_2 eq)	539,750	766,975	0.000	***
Other income (£)	108,948	66,910	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

[30] Source: Own calculations based on data from DEFRA (2008a, 2008b, 2010, 2011, 2014b, 2014c); Duchy College (2014, 2015, 2016, 2017)

b) 2010

	Cluster 1 (Less Intensive Farms)	Cluster 2 (Intensive Farms)		
	Mean	Mean	P-value	Sig
UAA (ha)	163	109	0.000	***
Labour input (hrs)	7,028	7,725	0.001	***
Feed (£)	82,359	135,153	0.000	***
Cows (No.)	110	170	0.000	***
Other costs (£)	149,020	181,802	0.000	***
Milk produced (hl)	6,951	13,004	0.000	***
GHG emissions (kg CO_2 eq)	547,314	811,438	0.000	***
Other income (£)	181,674	122,039	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

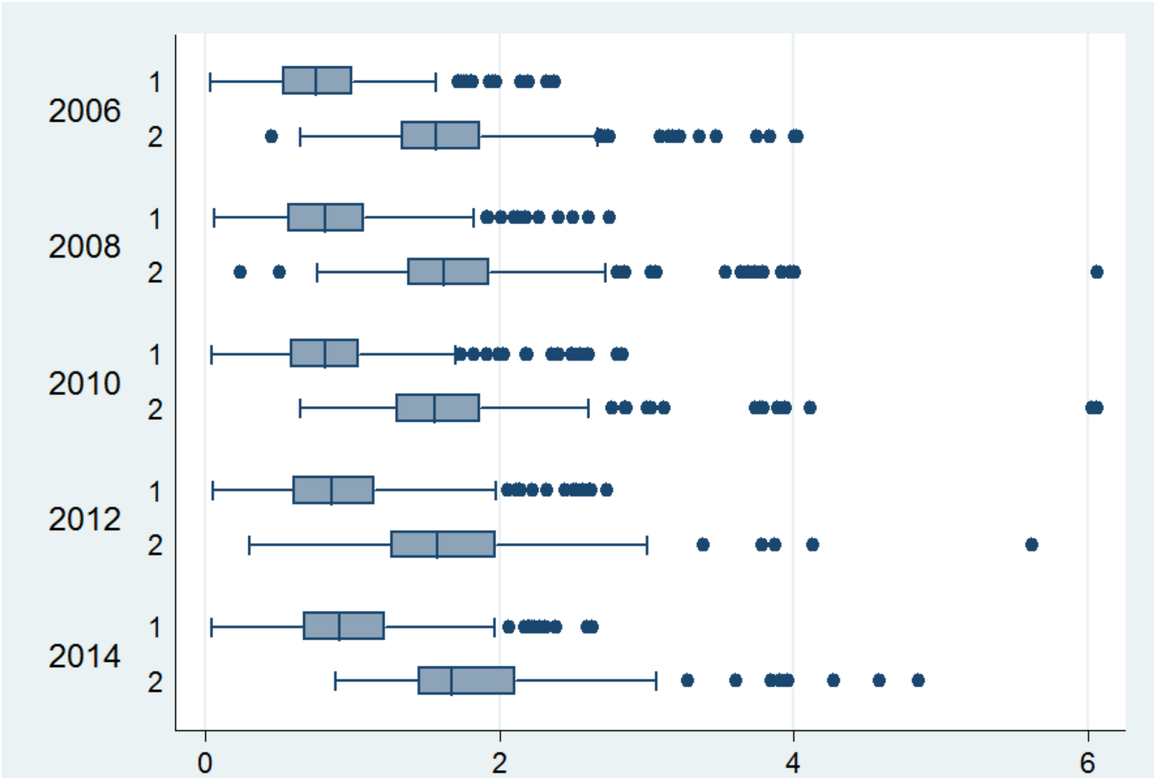
c) 2012

	Cluster 1 (Less Intensive Farms)	Cluster 2 (Intensive Farms)		
	Mean	Mean	P-value	Sig
UAA (ha)	159	110	0.000	***
Labour input (hrs)	7,105	7,890	0.000	***
Feed (£)	82,059	140,865	0.000	***
Cows (No.)	117	172	0.000	***
Other costs (£)	142,359	176,665	0.000	***
Milk produced (hl)	7,414	13,462	0.000	***
GHG emissions (kg CO_2 eq)	591,266	770,587	0.000	***
Other income (£)	161,612	111,577	0.000	***

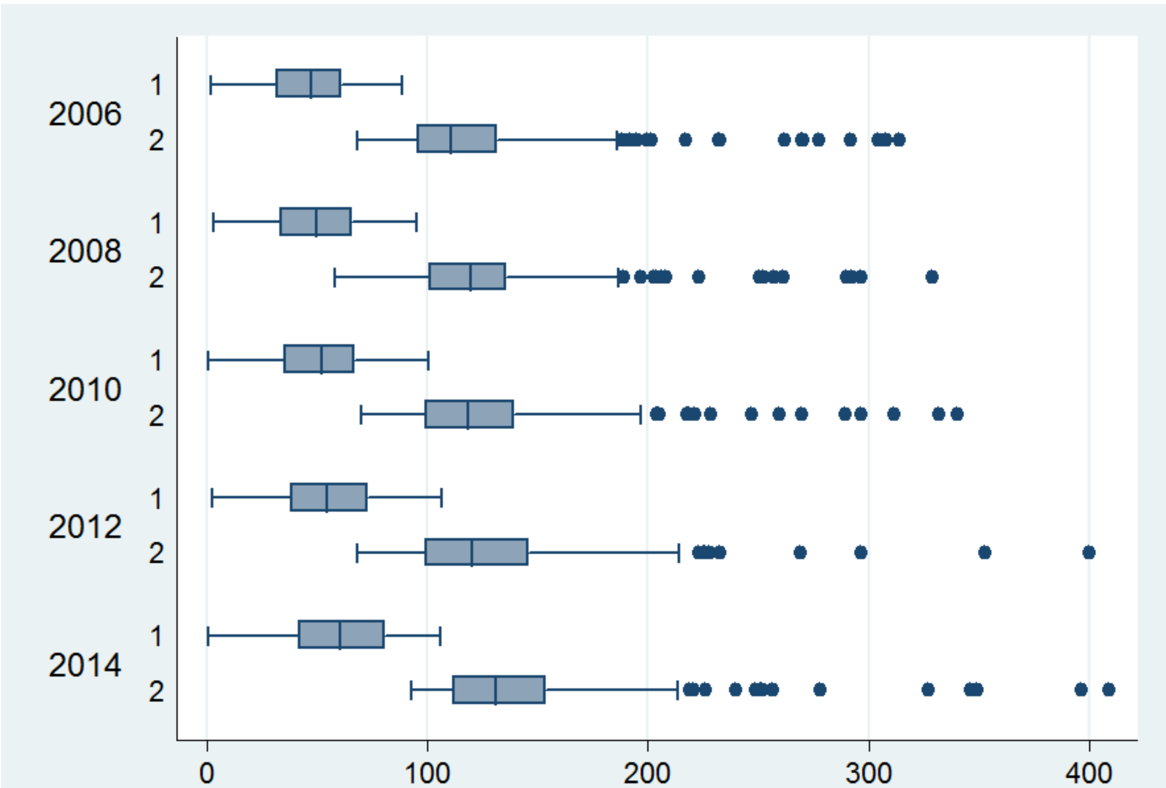
Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

Appendix 6. 4: Box and Whiskers plot for cluster varaibles

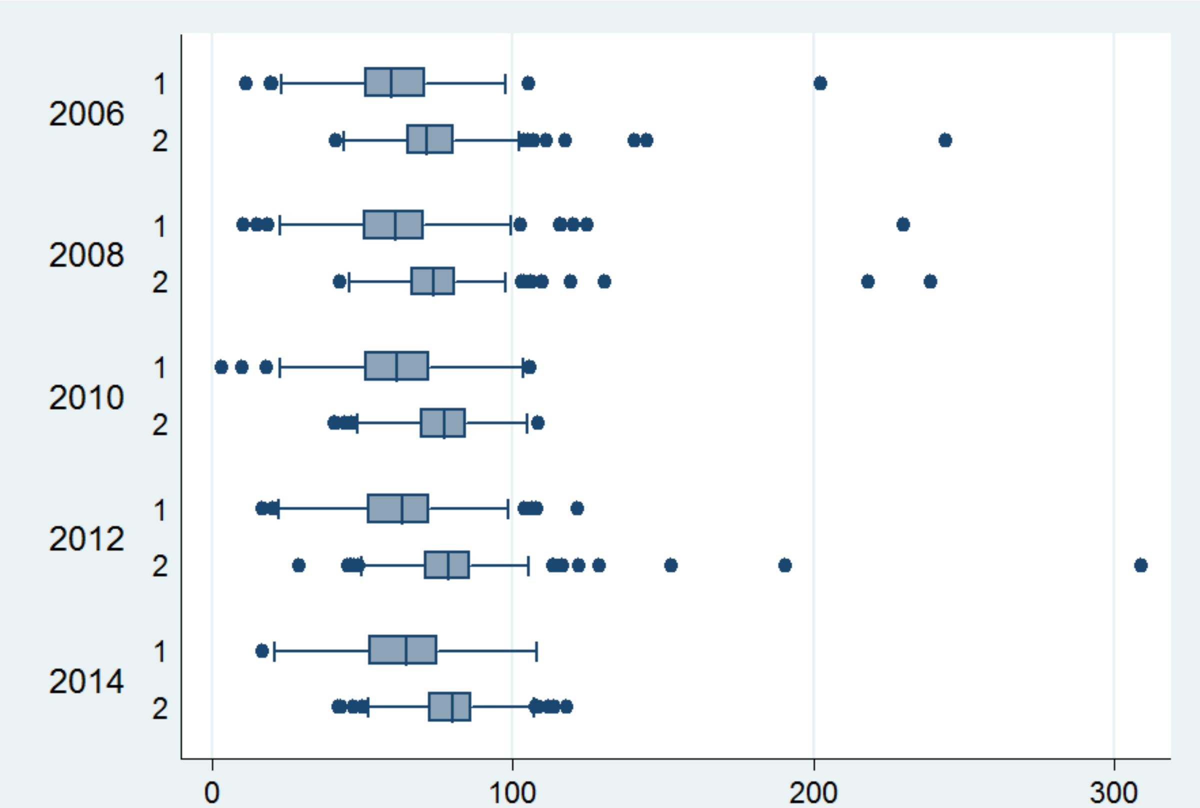
a) Stocking Intensity (cows/hectare)



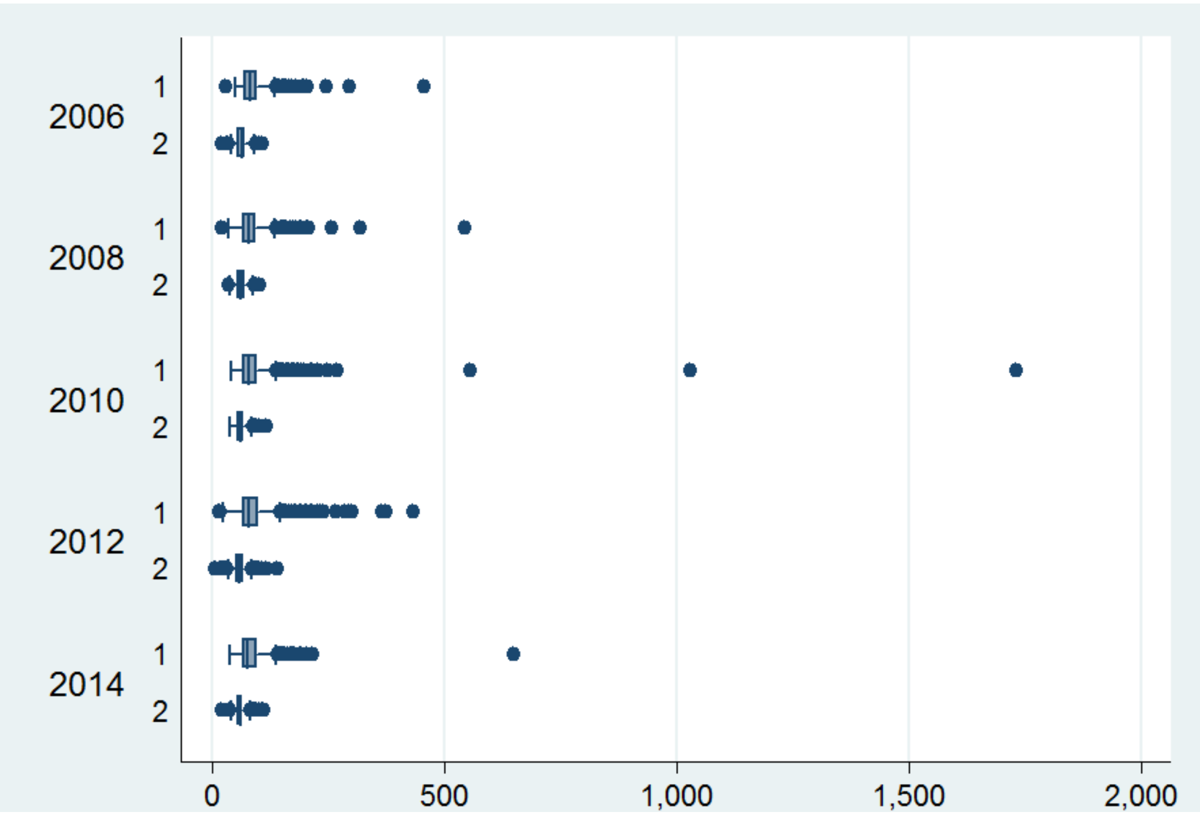
b) Milk per hectare (hl/ha)



c) Milk per cow (hl/cow)



d) GHGE per hectolitre of milk (kg CO_2 eq/hl)



Appendix 6. 5: Characteristics of technically efficient and inefficient farms (2008, 2010 and 2012)[31]

a) 2008

	TE > 1	TE = 1		
	Mean	Mean	P-value	Sig
UAA (ha)	138	167	0.148	
Labour input (hrs)	7,187	8,114	0.721	
Feed (£)	53,833	64,527	0.575	
Cows (No.)	128	154	0.683	
Other costs (£)	80,140	119,034	0.828	
Milk produced (hl)	8,459	11,366	0.020	**
GHGE (kg CO_2 eq)	603,398	725,428	0.541	
Other income (£)	83,105	147,488	0.695	
Stocking Intensity (cows/ha)	1.13	1.38	0.009	***
Milk produced per ha (hl/ha)	73	100	0.000	***
Milk produced per cow (hl/cow)	64	76	0.000	***
GHG per milk produced (kg CO_2 eq/hl)	79	72	0.000	***
No of obs	722	149		

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

[31] Source: Own calculations based on data from DEFRA (2008a, 2008b, 2010, 2011, 2014b, 2014c); Duchy College (2014, 2015, 2016, 2017)

b) 2010

	TE > 1	TE = 1		
	Mean	Mean	P-value	Sig
UAA (ha)	135	171	0.537	
Labour input (hrs)	7,061	8,853	0.027	**
Feed (£)	99,397	134,184	0.129	
Cows (No.)	126	187	0.003	***
Other costs (£)	149,014	244,244	0.005	***
Milk produced (hl)	8,770	13,695	0.000	***
GHGE (kg CO_2 eq)	616,022	905,055	0.002	***
Other income (£)	141,738	246,351	0.001	***
Stocking Intensity (cows/ha)	1.14	1.49	0.000	***
Milk produced per ha (hl/ha)	78	107	0.000	***
Milk produced per cow (hl/cow)	67	73	0.000	***
GHG per milk produced (kg CO_2 eq/hl)	80	84	0.000	***
No of obs	804	135		

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

c) 2012

	TE > 1	TE = 1		
	Mean	Mean	P-value	Sig
UAA (ha)	132	188	0.070	*
Labour input (hrs)	7,210	8,803	0.214	
Feed (£)	101,365	133,524	0.111	
Cows (No.)	134	174	0.342	
Other costs (£)	145,190	228,261	0.012	**
Milk produced (hl)	9,357	12,987	0.014	**
GHGE (kg CO_2 eq)	649,436	752,849	0.541	
Other income (£)	126,223	243,491	0.000	***
Stocking Intensity (cows/ha)	1.20	1.28	0.718	
Milk produced per ha (hl/ha)	82	94	0.186	
Milk produced per cow (hl/cow)	68	77	0.001	***
GHG per milk produced (kg CO_2 eq/hl)	79	73	0.000	***
No of obs	782	118		

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

7. EFFICIENCY ANANLYSIS OF THE DAIRY FARMS IN THE UK REGIONS: A TWO STAGE APPROACH

7.1. Introduction

The objective of this chapter is two fold.. Firstly, we assess the technical efficiency of dairy farms in the UK using Data Envelopment Analysis (DEA). Secondly, we explore the relationship between technical efficiency and farm specific variables by means of Tobit regression analysis to determine the drivers of efficiency. The Tobit regression would help us answer the third research question in which we want to determine the kind of factors that contribute to the efficiency of the farms.

DEA is a non-parametric approach to measure relative efficiency by considering the relationship between multiple inputs and multiple outputs. Then Tobit regression is used to explain the variations in efficiency scores of the farms. Understanding the relationship between the farm characteristics and efficiency is important and later in the thesis we work to provide policymakers with information needed to understand the practicalities involved with an increase in dairy intensification.

The farm specific variables that are taken to explain efficiency are the age and education of the farmer, the intensity of the farm, the gross value added (GVA) of the region in which a farm is located, the amount of loans, the cost of land, the tenure of the farm implying if the farm is tenanted or operated by the farmer and lastly the region in which a farm is located. We found that the age, loans and intensity of the farm positively influenced efficiency and the GVA and the cost of land negatively affected efficiency.

The structure of this chapter is as follows. The efficiency of dairy farms using DEA is estimated in Section 2. This section also explains the methodology and describes the data used for efficiency measurement. In section 3, the regional variations in efficiency are examined. In section 4 the factors that influence the farm's efficiency are discussed using Tobit regression. Lastly, section 5 concludes the chapter.

7.2. *Estimating Efficiency*

7.2.1. Methodology

The dairy producers combine multiple inputs such as land, labour and feed to produce outputs such as milk and milk products. In recent years, the costs of inputs have risen but with little or no increase in the price of milk. This has led producers to become more efficient in the way that they combine inputs to produce outputs.

It is not easy for the producers to determine the correct combination of inputs which might produce maximum output. Indicators such as milk produced per animal or cost of milk produced per unit are helpful in determining efficiency of a farm. These indicators are widely used as benchmarking policies to identify best practice. However, Fraser, I. and Cordina, D. (1999) argued that these partial indicators can provide spurious results. Taking an example of the costs of milk produced per unit, an increase in this ratio might be due to an increase in total cost, due to a decline in milk production or a combination of both. Thus, to assess efficiency by analysing partial indicators is inadequate (Wossink, A. and Denaux, Z. S. 2006).

To measure efficiency correctly, it is necessary to consider all inputs used and outputs produced by a farm, simultaneously. In economics and management science there are different methods of estimating efficiency.

Two widely used methods are the parametric and non-parametric approach. In a parametric approach, a production function is defined and an assumption on the distribution of error term is required. This method is known as Stochastic Frontier Analysis (SFA). However, in a non-parametric method a production function is not defined. Furthermore, one does not need to assume the distribution of the error term. This method is known as Data Envelopment Analysis (DEA). It is a linear programming methodology based on work by Farrell, M. J. (1957). DEA is a relative efficiency measure that constructs an efficiency frontier based on the firms' inputs and outputs. If a farm is on the frontier, then the firm is deemed as efficient. If a firm lies above or below the frontier then that firm is inefficient.

In this chapter output-oriented DEA is used to assess efficiency. The methodology employed to estimate technical efficiency is described in Chapter 4.6.2.2. The output-oriented technical efficiency, ϕ takes a value from 1 to infinity. The value of 1 represents technical efficiency where the farms are using their inputs in such a manner that maximised their outputs. A value greater than 1 indicated the possible expansion in outputs that could be achieved using the same level of inputs.

The technical efficiency of the output-oriented DEA used in this chapter is defined as an inverse of the parameter ϕ:

$$TE = \frac{1}{\phi}$$

Then the output-oriented technical efficiency takes the value of 1 if the farm is technically efficient and a value of less than 1 if the farm is technically inefficient.

Few studies on the dairy industry use input-oriented DEA models (Barnes, A. P. 2006; Stokes, J. R. et al. 2007). A rationale for adopting an output-oriented DEA is the abolishment of the milk quota system. In 2015, the EU abolished milk quotas to boost exports. The quota system was introduced in response to high milk production. Levys were charged to producers and purchasers who exceeded their quota limits (McNamara, K. 2017). In this situation, input-oriented models would have suited when the outputs were fixed and the efficiency of farms could be improved by reducing the inputs used. However, with the removal of quotas, there are no restrictions on the production of milk. It has become more important to maximise output with current inputs. Therefore output-oriented DEA is used which allows us to see how much milk could have been produced if there were no restrictions in place on the production of milk.

7.2.2. DEA inputs, outputs and data

The data were taken from the Farm Business Survey (FBS) for years 2006-2015. Farms in the sample have dairy herds of greater than or equal to 20 dairy animals (Stokes, J. R. et al. 2007). This resulted in a data set of 4505 decision making units (DMUs) as the number of farms varied over the years. DMUs

The variables used for inputs are the utilised agricultural area (UAA); labour hours; the cost of feed; the number of dairy animals and other costs. Milk produced and other income generated on a farm are taken as outputs. So, the input/output relationship is:

$$y(milk, other\ income) = x(uaa, labour, feed, cows, other\ costs)$$

Where y is a general output function with milk and other income production arguments and UAA, labour, feed, cows, and other costs are input function's arguments.

The descriptive statistics of input and output variables are given in Table 7.1.

Table 7. 1: Descriptive Statistics (N=4505)

	Mean	SD	Min	Max
UAA (ha)	140	117	19	1,278
Labour Hours (hrs)	7,335	3,921	1,612	41,340
Feed (£)	87,546	76,963	1,307	656,875
Cows (no.)	135	90	20	896
Other costs (£)	136,553	141,840	255	2,812,816
Milk Produced (hl)	9,386	6,833	167	57,081
Other income (£)	130,913	151,029	352	3,289,139

Source: DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

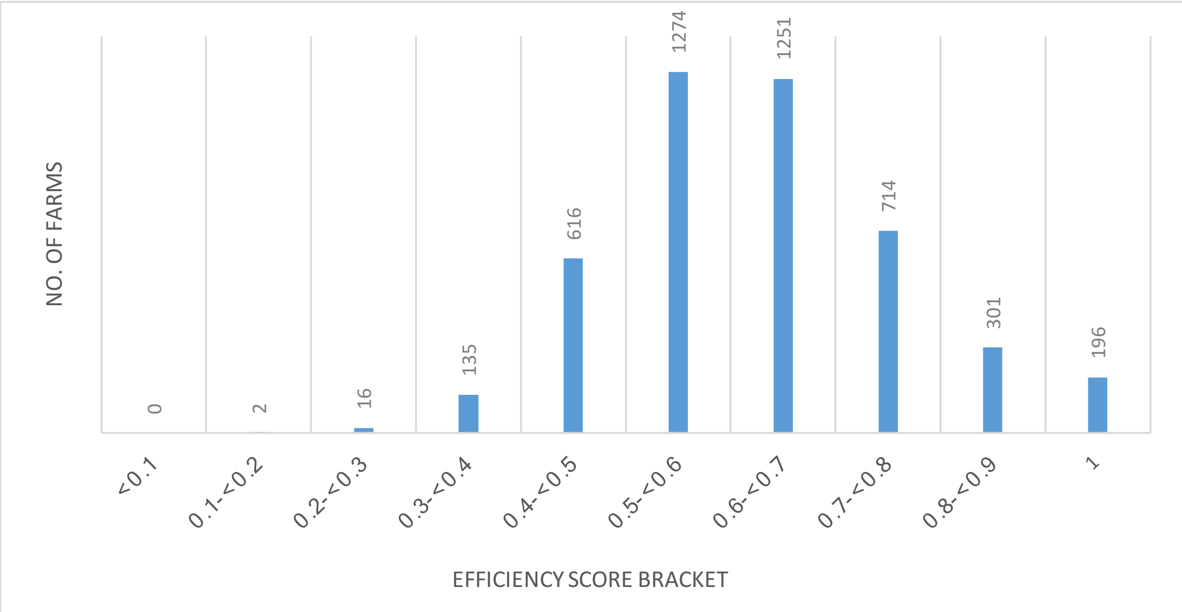
The average farm size was 140 hectares. The smallest farm in the sample was 19 hectares and the largest farm was 1,278 hectares in UAA. The average time spent working on a farm was 7,335 hours and the average cost of feed was £87,546. The farms in the sample had a herd size of 135 cows and the smallest herd size was of 20 cows. Largest farm in sample had a herd size of 896 cows. Milk produced by an average farm was 9,386 hectolitres and other income generated on a farm was £130,913.

7.2.3. Identifying efficient dairy producers

A VRS DEA was used to estimate the efficiency of farms in the UK over the 10-year period. All the years were combined to increase the sample size. This was done to increase the power of the statistical test. The DEA scores reported are between 0 and 1. The DEA Frontier is used to estimate efficiency. It reports scores for output oriented models from 1 to infinity, indicating the percentage of output it needs to increase to achieve efficiency. To make analysis simpler, the inverse of these scores is taken to bind them between 0 and 1. A score of 1 indicates that a DMU, in this case a farm, is technically efficient and does not need to increase its output production.

The results of the DEA are presented in Figure 7.1.

Figure 7. 1: Efficiency score bracket of farms



196 farms out of 4505 were identified as efficient farms, i.e. they did not have any input or output inefficiencies having a DEA score equal to 1. None of the farms had an efficiency score below 0.1999.

Only 2 DMUs' in the sample were in the efficiency score bracket of 0.1- < 0.2. Approximately, 3% of the farms in the sample had an efficiency score of 0.3 - < 0.4 implying they could increase their output production by more than 100%. The largest percentage of the farms belonged to 0.5 - <0.6 efficiency score bracket and 28% of the farms were sorted into this efficiency score bracket. The second highest number of farms were in the 0.6 - <0.7 efficiency score bracket (28% of the farms[32]).

The average technical efficiency score for the dairy farms in the sample was 0.72 implying that the farms were producing 72% of the output using the same level of inputs and could potentially increase their output production by 39%. According to the literature, the average technical efficiency score of dairy farms has generally been on the higher side. Barnes, A. P. (2006) found that overall technical efficiency score for the dairy industry in Scotland was 0.84 which was considered quite high and 30% of the sample farms were technically efficient. Compared to this only 4.6% of the farms in the sample were found to be technically efficient. However, Barnes, A. P. (2006) used input- oriented DEA models with different variables and data set. The number of technically efficient farms under input-orientation and output-orientation are

[32] Percentages have been rounded

alike as the frontier is the same for both the models (Coelli, T. J. et al. 2005). As mentioned before, DEA is a relative efficiency measure so differences in sample size and input and output variables would change the results. The Barnes, A. P. (2006) study used a sample of only 61 dairy farms in Scotland for DEA efficiency measure. Fewer DMUs would also cause biased results as the number of efficient DMUs would increase and the average efficiency is going to be higher (Alirezaee, M. R. and Panne, M. H. 1998).

The characteristics of an average efficient and inefficient farm are given in Appendix 7.1 It was interesting to see that the average farm size for both efficient and inefficient farms was 140 ha. Labours worked more on efficient farms as these farms had a larger herd size. Furthermore, these farms produced more milk but spent less on feed. Technically efficient farms also earned more from other activities on the farm.

However, a comparison like this is not accurate. To accurately compare the efficient and inefficient farms, we need to have a standard comparison. To gain a standard comparison between both farm types, all inputs and outputs are expressed as a ratio per dairy cow. A Mann-Whitney U test was used to determine whether there were significant differences between the two groups or not. Table 7.2 provides information on inputs and outputs per cow for efficient and inefficient farms. The last row provides the p-values obtained from the Mann-Whitney U test.

Table 7. 2: Farm characteristics per cow for technically efficient and inefficient farms

	UAA (ha)	Labour Hours (hrs)	Feed (£)	Other costs (£)	Milk Produced (hl)	Other income (£)
TE = 1	0.93	51	540	990	77	1,156
TE <1	1.04	55	654	1,013	69	961
P values	0.000	0.018	0.000	0.001	0.193	0.001
Sig	***	**	***	***		***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The UAA per cow was found to be significantly different for efficient and inefficient farms even though the total area of farms was the same. Efficient farms had a higher livestock intensity, having one dairy cow per 0.93 hectares of area compared to 1.04 hectares per cow for inefficient farms. The farmers in the efficient farms spent fewer labour hours working on a farm as well as spent fewer labour hours per cow. The efficient farms also spent less on feed and other costs than inefficient farms and they earned more from other income as well. Furthermore, dairy cows on efficient farms produced more milk than inefficient farms. However, the differences in milk production per cow between technically efficient and inefficient farms were not statistically significant.

So, this tells us that even if the average area of a farm is the same for efficient and inefficient farms, the livestock intensity is much higher in efficient farms. These farms also performed better in terms of requiring fewer work hours, spending less on feed and other costs per cow and producing more milk and other income than inefficient farms.

It needs to be mentioned here that the greenhouse gas emissions (GHG) are not included in the efficiency estimation as a bad output in this chapter. The correlation of efficiency score obtained in this chapter and the GHG emissions per unit of milk calculated in Chapter 5 was found to be negative implying that with the increasing efficiency of the farms, the GHG per emitted per unit of milk produced would decline.

Furthermore, to solidify the relationship between efficiency and GHG emissions per unit of milk, we calculated the correlation of the technical efficiency scores obtained from using the undesirable DEA in chapter 6 with the simple output-oriented DEA used in this chapter. The correlation in efficiency scores was only examined for the farms that reported their financial data in all years in the FBS.

The estimates of efficiency obtained from the undesirable DEA is based on the creation of frontiers for different years in the sample. However, the efficiency estimates derived in this chapter are determined by combining all the years into one year and constructing a single frontier. So we cannot compare the efficiency scores directly. To overcome this problem, the average efficiency score from the undesirable DEA and the simple output-oriented DEA were calculated for the farms that reported their financial data in the FBS for all the years. We found a positive correlation between the two efficiency scores[33]. It implies that the factors that may influence technical efficiency also affect the efficiency estimates obtained when including GHG emissions in the efficiency estimation.

[33] The efficiency scores obtained from the undesirable DEA in Chapter 6 have been taken as inverse to bind them between 0 and 1 where 0 implies inefficiency and 1 implies efficiency.

The results of DEA not only tell us which farms are efficient and which are not, but it also identifies benchmarks or peers of inefficient farms. These peers of inefficient farms are technically efficient farms that the inefficient farms could mimic to become efficient. Benchmarking is another way for the inefficient farms to become efficient (Stokes, J. R. et al. 2007). Identifying and studying the benchmarks for inefficient farms would help them to determine changes that could be made to achieve efficiency. The DEA Frontier gives the percentage by which the inefficient farms need to mimic the efficient farm. These benchmarks can help us determine changes that need to be made to the inefficient farms for them to become efficient. An inefficient farm can have more than one peers as shown in Table 7.3 which reports the benchmark DMUs for the five least inefficient farms and the five most inefficient farms.

The inefficient farms have up to 7 benchmark DMUs which are the efficient farms. Taking an example of DMU 2304, it has an efficiency score of 0.23 making it the most inefficient farm in our sample which is indicated by the rank given to this DMU. The DMU 2304 has 7 benchmark DMUs and these benchmarks farms are those that have similar production mix to the said farm (Rouse, P. et al. 2009). The percentage associated with the benchmark DMU indicates its relative importance to the DMU. So, for DMU 2304, the benchmark DMU 1727 has the most importance as the inefficient DMU needs to mimic 51.7% of the benchmark DMU's output.

Table 7. 3: Benchmarking DMUs for inefficient farms

			Benchmarks													
			1		2		3		4		5		6		7	
Rank	**DMU**	**Eff. Score**	**DMU**	**%**	**DMU**	**%**	**DMU**	**%**	**DMU**	**%**	**DMU**	**%**	**DMU**	**%**	**DMU**	**%**
197	**759**	0.999	512	0.112	860	0.143	1321	0.144	1653	0.144	3509	0.355	4426	0.102		
198	**574**	0.999	822	0.333	1750	0.075	1783	0.135	2114	0.398	4092	0.059				
199	**1641**	0.999	512	0.051	1459	0.409	1599	0.161	1684	0.372	2626	0.006				
200	**2331**	0.999	512	0.008	781	0.055	860	0.044	2072	0.535	3509	0.181	4426	0.177		
201	**1305**	0.998	512	0.063	567	0.115	781	0.334	2072	0.395	2626	0.093				
4501	**46**	0.332	512	0.071	935	0.279	1171	0.087	1459	0.404	1832	0.008	1952	0.151		
4502	**1373**	0.321	1543	0.576	1656	0.076	1727	0.222	2983	0.125						
4503	**2987**	0.302	512	0.054	567	0.105	1459	0.161	1656	0.200	1832	0.410	2202	0.057	2626	0.013
4504	**1649**	0.256	310	0.088	798	0.015	1730	0.142	1744	0.077	2047	0.678				
4505	**2304**	0.238	512	0.034	567	0.097	820	0.039	1459	0.225	1656	0.062	1727	0.517	2294	0.026

It should be noted that benchmark identification depends on the dataset. So if a best practice farm is not included in the sample, DEA would not be able to benchmark inefficient farms against it (Huysveld, S. et al. 2017). There may also be other reasons why the benchmark farms have a higher efficiency score (equal to 1) than the DMU 2304 which is not captured by the inputs such as animal breed, farm management and feeding practices, age and education of the farmer etc. To evaluate the factors that may contribute to the increase in efficiency of the benchmark DMUs, the Tobit Regression is undertaken in Section 7.4.

7.3. Regional variables

The classification of regions is done according to the Classification of Territorial Units for Statistics (NUTS). It is used for referencing a subdivision of countries for statistical purposes and is regulated by the European Union. There are three levels of NUTS. NUTS 1 is the highest tier of the division of the country. Currently, in the UK, there are 12 NUTS 1 territories. 9 of them are regions in England and the others are Wales, Scotland and Northern Ireland as a whole.

For the purpose of my study, I have taken NUTS1 as a way of classifying regions. Since this research is focused on England and Wales, it has reduced the number of regions from 12 to 10. Furthermore, the region of Greater London does not have any dairy farms so this region has been excluded from the study. This leaves 9 regions.

North East

The average farm size in the North East is 139 hectares. This region has the smallest number of agricultural holdings but has the largest average farm size. The farm type dominating this region is grazing livestock which accounts for 56% of the total agricultural holdings followed by 18% of cereal crop farms. Only 2% of the total agricultural holdings in North East were dairy farms making it the second to the last region with regards to dairy farm numbers.

North West

The average farm size in North West was 75 hectares. The largest portion of dairy farms in England was found in the North West where 13% of all agricultural holdings were dairy farms. The farms in North West were dominated by Grazing livestock farms which accounted for 57% of the total agricultural holdings. Around 25% of the dairy herds in England were present in the farms in North West. North West had the smallest percentage of cereal crop farms in all regions in England.

Yorkshire

The average farm size in Yorkshire was 90 hectares. The dominant farm type in Yorkshire was grazing livestock (42%) followed by cereal crop farms (21%) of all agricultural holdings. There were 12,171 agricultural holdings in Yorkshire but only 5% of these holdings are dairy farms.

East Midlands

The average farm size in the East Midlands was 100 hectares. Approximately 36% of all agricultural holdings in East Midlands were grazing livestock farms followed by cereal crop farms (21%). Only 4% of all agricultural holdings were dairy farms.

West Midlands

The average farm size in the West Midlands was 66 hectares making it the region with the smallest farms in terms of area. However, West Midland had the second highest number of agricultural holdings in England. West Midlands had 13,724 agricultural holdings and 7% of these holdings are dairy farms. West Midlands was dominated by grazing livestock farms which accounted for 47% of all agricultural holdings.

East of England

The average farm size in East of England was 116 hectares and 38% of all agricultural holdings in this region were cereal crop farms. East of England had the smallest percentage of dairy holdings amongst all the regions in England.

South East

The average farm size in the South East is 89 hectares. The largest portion of agricultural holdings in South East was grazing livestock (43%) followed by cereal crop farms (18%) only 3% of the agricultural holdings in South East were dairy farms

South West

The average farm size in the South West was 69 hectares making it the region with the second smallest average farm size amongst the regions in England. However, South West had the highest number of agricultural holdings in England. Grazing livestock farms made 51% of all agricultural holdings in South West making it the dominating farm type in this region. Approximately 10% of all holdings were dairy farms making it the second largest region with dairy holdings.

We found that the predominant agricultural holdings in England were of grazing livestock farms that made up 44% of all agricultural holdings and covered 29% of the total agricultural land in England. It was followed by cereal crop farms that made up 17% of the total agricultural holdings but had the largest share of land (33%) in England. Dairy farms only accounted for 6% of all agricultural holdings and covered 10% of the total agricultural land in England.

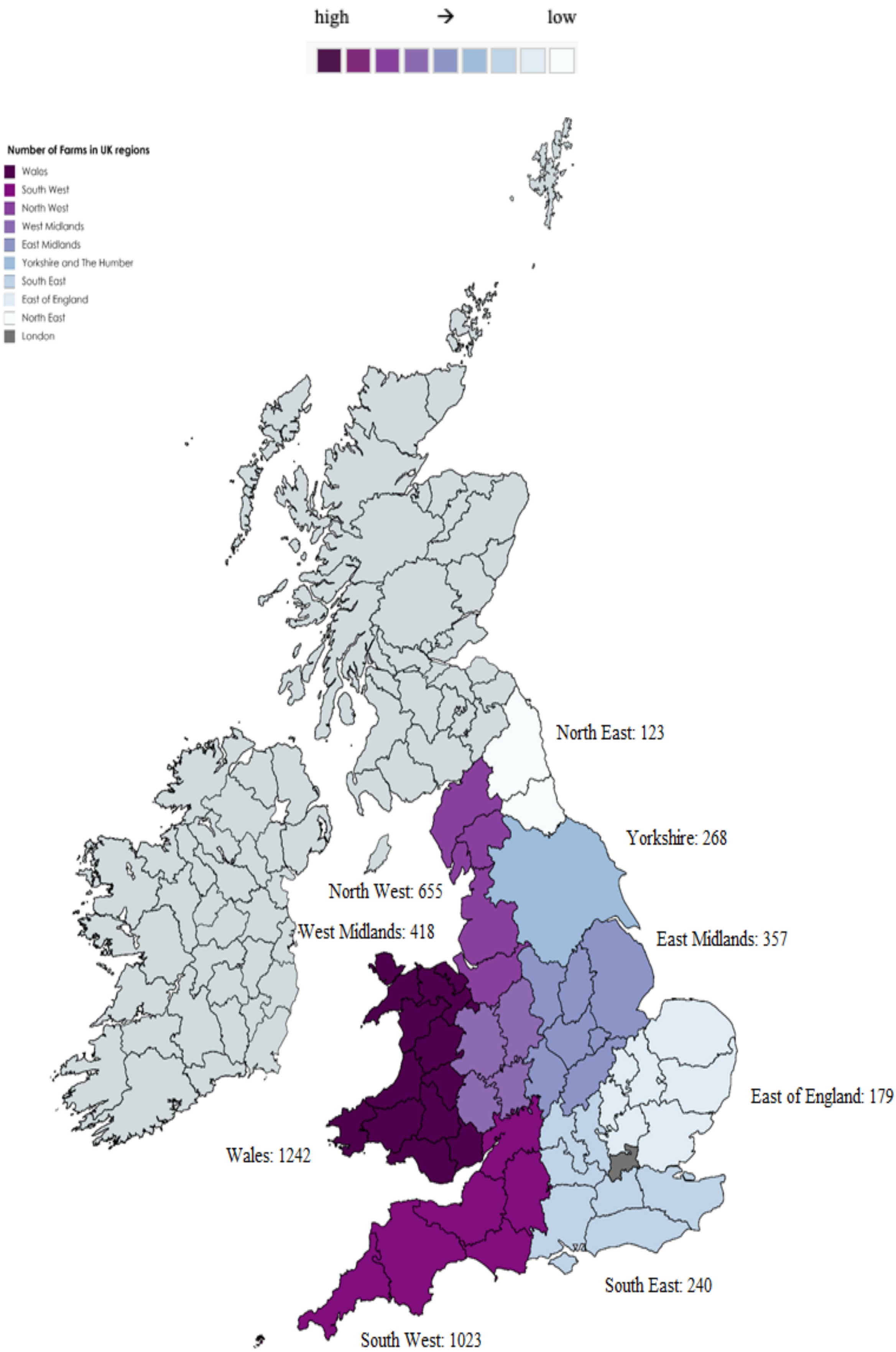
Since the main focus of this thesis is dairy farms, we would use data from the FBS to investigate the characteristics of dairy farms in these regions. Figure 7.2 presents the number of dairy farms in our sample data.

In the sample, Wales has the largest number of dairy farms since Wales has not been divided into its counties. The South West has the second largest numbers of farms. North East is the region with the least number of farms. The farms with dairy cows are concentrated towards the west of the UK. So, the FBS, although a small sample of the population, accurately reflects the distribution of dairy farms in England.

The descriptive statistics of an average farm in a region in the UK is given in Appendix 7.2.

The average farm's size of the full sample was 140 ha. The five regions, North East, North West, Yorkshire, West Midland and Wales had farm size less than the average. Among these regions, Wales had the smallest farm size in terms of area, averaging 114 hectares per farm. The largest farms in terms of the area were present in South East where an average farm was 264 hectares. The herd size varied of farms from region to region. The largest herd size of a farm was 264 cows which were located in the South East and the smallest herd per farm was located in North East with only 90 cows. The largest farms in term of the area would have a larger herd size as they have more space to accommodate the animals.

Figure 7. 2: Number of Dairy Farms in UK regions



However, due to differences among the average size of the farms, the other input variables would also differ and so we cannot make an accurate comparison. To compare the use of inputs in different regions, we analyse the input usage per cow which is presented in Table 7.4.

Table 7. 4: Farm characteristics per cow for regions

Regions	Cows (No.)	UAA (ha)	Labour Hours (hrs)	Feed (£)	Other costs (£)	Milk Produced (hl)	Other income (£)
North East	90	1.31	60	705	1,126	68	1,239
North West	133	1.32	59	712	853	69	936
Yorkshire	121	1.24	64	650	879	69	1,010
East Midlands	124	1.23	68	633	945	70	1,107
West Midlands	118	1.27	71	664	1,028	68	1,213
East of England	148	1.49	76	746	1,477	78	1,678
South East	179	1.54	75	632	1,371	72	1,529
South West	147	1.18	68	590	1,019	67	1,144
Wales	132	1.08	55	603	879	65	951

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

In the farm in the South East, there is one cow per 1.54 hectares of land making it the region with the highest area per animal. An average farm in Wales contained one cow per 1.08 hectares making it the region with least area per animal.

The farms in Wales spent 55 hours per cow, followed by the farms in North West. The higher number of labour hours worked per cow on a farm were 76 and 75 hours in East of England and South East respectively. We find a positive correlation[34] between the area per cow and the labour hours per cow. It is intuitive as having less area per cow would reduce the labour hours worked per cow on the farm due to their proximity to each other. The total cost of feed per cow varied between the regions ranging from £590 to per cow in the South West to £746 per cow in the East of England. The differences in the cost of feed per cow could be due to the different quality of the feed, its content, procurement practices of the farm or the quantity of feed that a particular cow consumes.

The other cost per cow ranged from £1,477 in East of England to £853 in North West. The other costs include all other costs that have not already been taken as input costs. The milk

[34] Correlation coefficient between UAA/cow and labour hours/cow is 0.6156

produced per cow was the higher in East of England amounting to 78 hectolitres of milk per cow. The least amount of milk produced per cow was in Wales which was 65 hectolitres per cow. Other income per cow was also higher in East of England compared to the rest of the regions. The lowest other costs per cow was in the North West.

Just by looking at Table 7.4, we can determine that the farms in East of England produced more milk and generated higher other income per cow while having a higher cost of feed and other costs. The farms in East of England also used more labour hours per cow than the rest of the regions. So, overall the productivity of East of England looks to be higher than the productivity of other regions but it would have higher costs than other regions. Rather than comparing the productivity of these regions by using simple indicators, we can use DEA to measure efficiency to determine which farms in a region produce more output while using the correct proportion of inputs.

7.3.1. Regional Efficiency

The efficiency of farms in the sample was estimated using DEA. The average efficiency score for regions was calculated by taking an average of efficiency score of farms in that said region. A separate frontier was not created to estimate the efficiency of regions. The average efficiency of regions in the UK was calculated through a single frontier. As mentioned before, DEA is a relative efficiency measure. If a farm or a region is not included in creating a frontier, it cannot be compared with another frontier. So, if separate frontiers were created for all the regions then it would make it impossible for us to compare the efficiency of those regions as all the frontiers created would have different farms.

All regions had an average efficiency score greater than 0.70 which is backed up by literature that efficiency of dairy farms in generally higher (Barnes, A. P. 2006). Number of technically efficient farms in regions is also presented in Table 7.5.

Table 7. 5: Regional Efficiency

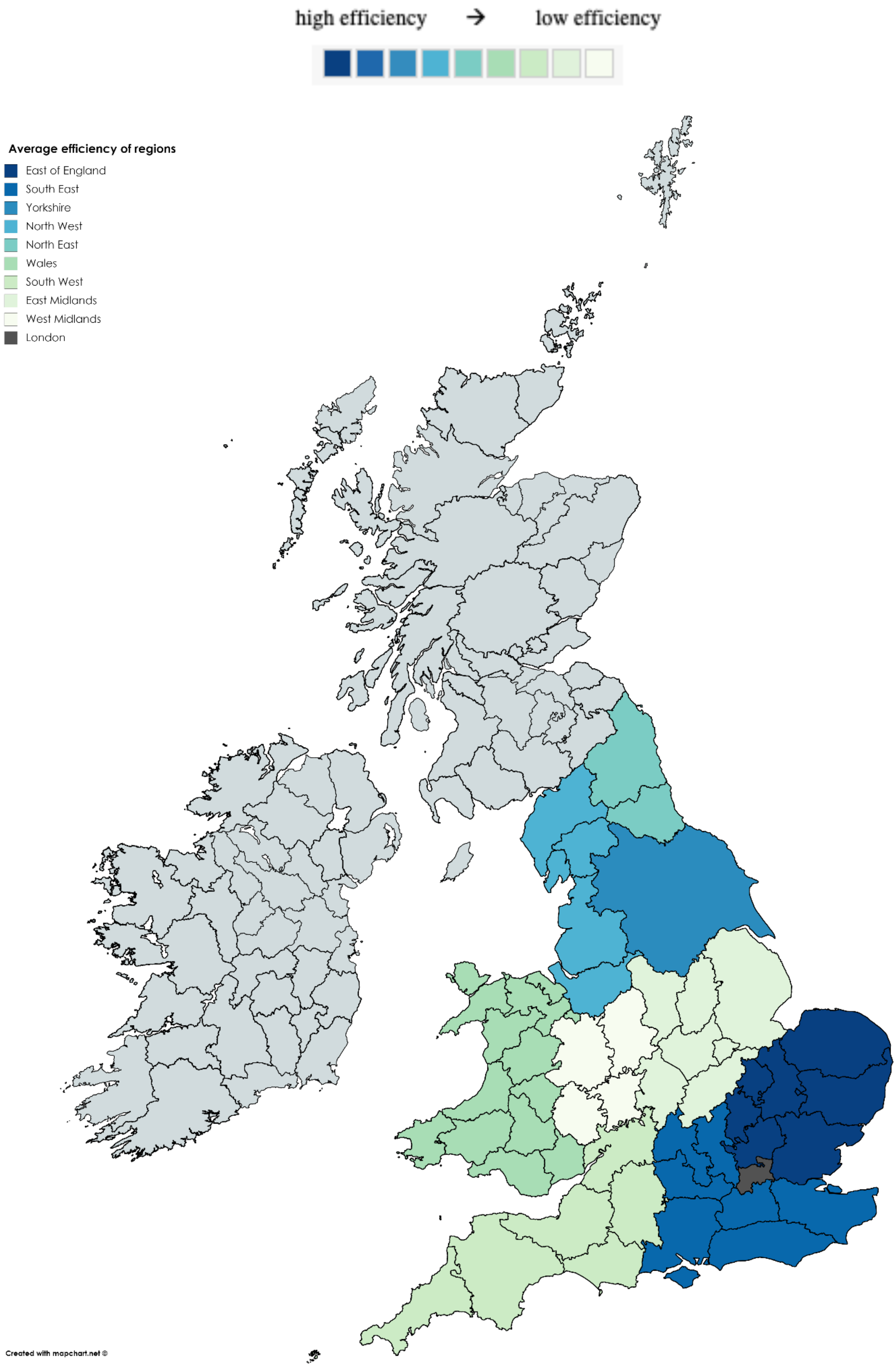
Region	Mean	SD	Min	Max	Efficient Farms
North East	0.731	0.112	0.535	1	5
North West	0.736	0.130	0.401	1	31
Yorkshire and The Humber	0.739	0.128	0.384	1	11
East Midlands	0.714	0.129	0.378	1	14
West Midlands	0.704	0.126	0.404	1	20
East of England	0.776	0.122	0.256	1	3
South East	0.749	0.132	0.428	1	10
South West	0.716	0.132	0.238	1	50
Wales	0.720	0.135	0.302	1	52
Total	0.725	0.132	0.238	1	196

The highest number of technically efficient farms are located in Wales followed by South West. These regions also have the highest number of farms containing dairy cows. Approximately 4.9% of all farms in the South West and 4.2% of all farms in Wales are technically efficient. North West and West Midlands also have a higher percentage of technically efficient farms (4.7% and 4.8%, respectively) compared to farms in the other five regions. Relatively fewer farms are technically efficient in the East of England. Only 1.6% of all farms in East of England are technically efficient. The technically efficient farms in regions is shown in a map in Appendix 7.3 and the average efficiency of regions is also shown on the map in Figure 7.3.

Even though Wales had a higher proportion of technically efficient farms, the average technical efficiency was the highest in East of England. We saw from Figure 7.2 that the dairy farms were concentrated towards the west of the UK however, the average efficiency of these regions is on the lower side.

Although fewer farms in East of England are technically efficient, this region overall has the highest efficiency score indicating that it needs to increase its output production least amongst all regions. The region of East of England produced the highest amount of milk per cow and generated the higher other income per cow. Despite this region having higher labour hours, feed costs and other costs per cow, it is using its inputs in a way that maximises its outputs.

Figure 7. 3: Average efficiency of the regions



East of England is followed by South East which has 4.2% efficient farms but average efficiency is 0.749. Lowest average efficiency is of farms in the West Midlands even though 4.8% of all farms are technically efficient. This shows that large differences exist in efficiency score between farms in this region. Lowest efficiency score obtained belonged to a farm in the South West, followed by a farm in East of England.

We can see that the average efficiency of these farms creates a geographic grouping. The regions in the East (South East and East of England) have the highest efficiency score. It is followed by regions in the North (North West, North East and Yorkshire) who have second highest average efficiency. Lastly, regions in Midlands and West (East Midland, West Midland, Wales and South West) have the lowest average efficiency score.

The differences in efficiencies between regions may be due to differences in technology rather than in the way that they mix their inputs to produce outputs. So, the differences in efficiency scores between DMUs and regions could be due to variables not included in the DEA model. These variables could be linked to production, technology, business management and other aspects of the farm. So there may be a need to examine variables not included in the DEA model to understand how much they impact efficiency (Stokes, J. R. et al. 2007). In the next section of this chapter off-farm variables are examined that may influence efficiency using Tobit regression.

7.4. Explain inefficiency through Tobit regression

The previous section estimated the efficiency of farms using the DEA method. Efficient and inefficient farms were identified and the characteristics of efficient and inefficient farms examined. In this section, the DEA efficiency score computed in the previous section is regressed on factors that may be able to capture inefficiency. There are a variety of regression techniques that could be applied to estimate the impact of contextual factors on efficiency. The methods include ordinary least square (Nicholson, F. et al.) and maximum likelihood based probit, logit and Tobit regressions.

7.4.1. <u>Methodology</u>

To deal with latent variables, y^* which cannot be observed, probit and logit models are useful.

The regression model used then is:

$$y^* = x\beta + u$$

Assuming that there is only one dependent variable and that variable in logit and probit models is a dummy variable:

$$y = \begin{cases} 1 & if\ y^* > 0 \\ 0 & if\ y^* \leq 0 \end{cases}$$

Suppose that we have y^* which is observed if it is greater than 0 and not observed if it is less than or equal to 0. Then the observed y can be defined as:

$$y = \begin{cases} y^* = x\beta + u & if\ y^* > 0 \\ 0 & if\ y^* \leq 0 \end{cases}$$

And $u|x \sim Normal\ (0, \sigma^2)$.

This is known as a Tobit model. It was developed by Tobin, J. (1958) and is also known as censored normal regression model due to its property of censoring some observations on y^* (Maddala, G. S. and Lahiri, K. 2009). Tobit regression is used to understand variations in efficiency as the DEA scores fall between the interval 0 and 1, making the dependent variable (efficiency score) as a limited dependent variable.

The objective of the Tobit model is to estimate parameters β and σ. OLS cannot be used to estimate these parameters as the error term in Tobit models does not have a zero mean. Since the observations with $y^* \leq 0$ are omitted, it implies that only observations included in the sample are the ones for which $u > -x\beta$. Therefore, the distribution of u is a truncated normal distribution. Then the Tobit model used maximum likelihood (ML) to estimate β and σ.

7.4.2. Previous studies

The Tobit models are used to characterise the distribution of efficiency and in turn provide results that can be helpful in the improvement of efficiency (Tipi, T. et al. 2009). Tobit regression has been used to determine the relationship between efficiency and factors for a variety of sectors. Sağlam, Ü. (2017) used Tobit regression to test turbine specifications with the efficiency of wind farms in the US. Bai, Y. et al. (2018) used Tobit regression to estimate a relationship between thermal power firm's efficiency with some control variables.

Tipi, T. et al. (2009) used two–stage methods to estimate the technical efficiency of rice farms in Turkey. They used Tobit regression to determine the effects of non-farm factors such as age, farm size, the number of plots, off-farm income and membership of cooperative on a farm's efficiency. Their results showed that farm size and memberships had a positive while the number of plots, age and off-farm income has a negative relationship with efficiency.

A similar study was conducted by Poudel, K. L. et al. (2015) on coffee farms in Nepal. They used DEA to calculate technical efficiency and then in the second stage, they used Tobit to determine farm characteristics that may influence efficiency. They used off-farm variables such as household size, education, gender, training, age, farm experience and farmer's access to credit to explain differences in efficiency scores. Their estimated coefficients for most of the factors were positive but not significant. Age of farmer was the only factor that was significant.

Hansson, H. and Öhlmér, B. (2008) used Tobit regression to investigate how operational managerial practices such as animal health, breeding and feeding practices contribute to farms' technical efficiency. They found that breeding the exact number of cows needed for replacement had a negative effect on efficiency while foraging positively affected efficiency. Animal health practices had no significant effect on efficiency indicating that inefficient farms could not be more efficient by adopting health practices of efficient farms.

Sharma, K. R. et al. (1999) estimated the technical, allocative and economic efficiency of swine producers. They compared the results of efficiency obtained from parametric and non-parametric methods. They used farm-specific factors to assess the productive efficiency of these farms. The farm specific variable taken for the study were based on the size of the farm, education level of farmer, experience, types of pigs, feeding and location. Results of efficiency obtained from the parametric method were higher for constant returns to scale (CRS) model but the same as the non-parametric method for VRS model. They found that farm size had a negative and significant effect on inefficiency indicating that larger farms operated at a higher efficiency level. Larger farms performed better as they required less labour use per unit of output and lower feed price.

Barnes, A. P. (2006) used Tobit regression to determine the effect of farm multi-functionality on technical efficiency in the wake of changing Common Agricultural Policies. Multi-functionality here acts like the sustainability of a farm social, economic and environmental goals influence a farms' decisions. DEA was used to estimate the technical efficiency of Scottish dairy farms. In the second stage of analysis they used variables like herd size, farmer's membership of cooperatives, education level, years in farming and a multifunctional score. Size of the herd had a positive and significant effect on efficiency indicating that larger herds in Scotland were operating at higher levels of efficiency than smaller herds.

Similarly, years in farming had a positive and significant effect on efficiency. Results indicated that farmer's membership of co-operatives had an adverse effect on efficiency while education had a positive effect but both these results were insignificant. Lastly, multi-functionality had a positive and significant effect on efficiency.

Tobit regression was used by Shortall, O. K. and Barnes, A. P. (2013) to understand the impact of different dairy farm variables on the efficiency of dairy farms in Scotland. They included farm variables such as the number of dairy cows, milk output per cow, education of the farmer, number of years in farming and a dummy variable to represent whether they had joined an environmental scheme or not. The results showed that larger farms (higher number of dairy cows) were more technically efficient than smaller farms. The number of dairy cows was also highly correlated with litres of milk produced per cow. They found no significant relationship between farm efficiency and experience or years of education of a farmer. Lastly, there was a positive effect of environmental schemes on efficiency.

7.4.3. <u>Farm specific variables</u>

The estimated Tobit model is:

$$\begin{aligned} Eff = \beta_0 + \beta_1 AGE + \beta_2 EDU + \beta_3 INTE + \beta_4 LNGVA + \beta_5 LOANS + \beta_6 LNLANDCOST \\ + \beta_7 TENURE + \beta_8 dregion1 + \beta_9 dregion2 + \beta_{10} dregion3 \\ + \beta_{11} dregion4 + \beta_{12} dregion5 + \beta_{13} dregion6 + \beta_{14} dregion7 \\ + \beta_{15} dregion8 + u \end{aligned}$$

Where:

Eff: Technical efficiency score bound between 0 and 1.

AGE: Age of the farmer (continuous)

EDU: Dummy variable for education (Graduate/post graduate degree=1, Rest=0)

INTE: Dummy variable for intensive farms (Intensive farms=1, Less Intensive =0)

LNGVA: Log of Gross Value Added (£)

LOANS: Average loans of a farm (£)

LNLANDCOST: Log of cost of land per hectare (£)

TENURE: Dummy variable for ownership of farm (Owned = 1, Tenanted=0)

dregion1: Dummy variable for region 1 (North East=1, Otherwise=0)

dregion2: Dummy variable for region 2 (North West=1, Otherwise=0)

dregion3: Dummy variable for region 3 (Yorkshire=1, Otherwise=0)

dregion4: Dummy variable for region 4 (East Midlands=1, Otherwise=0)

dregion5: Dummy variable for region 5 (West Midlands=1, Otherwise=0)

dregion6: Dummy variable for region 6 (East of England=1, Otherwise=0)

dregion7: Dummy variable for region 7 (South East=1, Otherwise=0)

dregion8: Dummy variable for region 8 (South West=1, Otherwise=0)

The mean value of farm specific variables is presented in Appendix 7.4.

Age

The youngest farmer in the sample was aged 21 years and was located in Yorkshire whereas the oldest farmer was 92 years of age and was found in Wales. The average age differed across the sample. The average age of the farmer was the lowest in Yorkshire and North West (52 years). The highest mean age of the farmer was in the South East, and the average age was 57 years. The average age of a farmer in the sample was 54 years with four regions having farmers' older than the average and five regions having farmers younger than the average age.

Education

The educational variable is taken as a dummy which takes the value of 1 if the farmer has a graduate or a post graduate degree (hereafter referred to as just degree) and takes a value of 0 if he has other educational levels. Out of the 4505 farms, approximately 45% of the farmers had a degree whereas the remaining 55% had other qualifications. Among all the regions, the farms in East of England had the highest percentage of farmers with a degree (69%) and the lowest percentage of farmers with a degree were located in Wales (30%).

Intensity of farm

The intensity of a farm is taken as a dummy variable. It takes a value of 1 when a farm is intensive and 0 if a farm is less intensive. The intensity of a farm is determined by variables such as the number of cows per hectare, milk produced per cow and milk produced per hectare. Intensive farms produce more milk per hectare and per cow. In addition, these have a higher stocking intensity, meaning that they have a higher number of cows per hectare. To separate farms into clusters, K-means Cluster Analysis was employed as described in detail Chapter 6.

A total of 1,564 farms in the sample were classified as intensive farms which made 35% of all farms in the sample. Wales has the highest proportion of intensive farms. Approximately 42% of all farms in Wales are intensive farms. It is followed by North West and West Midland, having 39% and 37% or intensive farms, respectively. The lowest percentage of intensive farms were found in East of England where only 15% of all farms were intensive.

GVA

Gross Value Added (GVA) is a measure of the value of the economy due to the production of goods and services. The value of GVA is given on a per head basis and has been adjusted for inflation at 2015 price level. The regional estimates of GVA are taken from the Office of National Statistics (ONS). The ONS measures GVA using the income approach where income generated by individuals and corporations through the production of goods and services is added up. ONS estimates GVA based on workplace location. This is good for our analysis as we want to use GVA as an indicator of economic activity in that region. GVA is estimated in millions of pounds and divided by the resident population in that region to give GVA per head in pounds.

London has the highest GVA per head among all regions, but since London is not included in our study, we ignore it. For the regions in our analysis, South East had the highest GVA per head followed by East of England. North East and Wales had the lowest GVA per head among all regions indicating that less economic activity occurs in these areas.

Loans

The FBS reports opening and closing values of loans. Using the opening values would result in some farms having a zero opening value of loans. However, these farms may acquire loans later in the year which would not be represented if we take opening year's value. Similarly, if we take the closing value of the loans, then some farms might show zero loan amount, though it may not be true as they might have loans at the start of the year which they may have paid off by year-end. So, taking opening or closing values would not accurately represent the amount of loans

So, to make matters simple, I have taken the mid-year loans value to represent the loan amount. Loans are then calculated by:

$$\text{loans} = \frac{\text{opening value} + \text{closing value}}{2}$$

The loan amount can indicate the impact of financial risk and pressure on the farm (Zhu, X. et al. 2012). It can also indicate the willingness of a farmer to invest more in technology that many improve farm's efficiency (Barnes, A. 2008). The highest amount of loans per farm were in the South East followed by East of England. Least amount of loans was taken by farms situated in the North East.

Land Cost

We are interested in looking at the relationship between the prices of a hectare of farmland with efficiency. The FBS gives the area of the farm denoted in hectares and the £ value of UAA so calculating per unit price is simple. The total UAA is divided by the cost to get the value per hectare of land. Then natural logarithm is taken for the data.

A few farms in the sample did not report the cost of land in the FBS. For the farms that do not report the cost of the land, the value has been calculated manually by taking the average cost of land for that specific region. Average land value is then used as the cost of a unit hectare.

Looking at the cost of land, it was highest in the West Midlands where a hectare of farmland costs £10,056. The cheapest land was in the North East where per hectare of farmland was valued at £5,191. The average land price for the sample was £7,859.

Tenure

Tenure is taken as a dummy variable. The FBS provides three categories for tenure which are tenanted, owner-occupied and mixed farms. Since we have taken a dummy for tenure, mixed farms are considered as owner-occupied since the owner of a farm is engaging in farm activities. So, owner-occupied farms are classified as 1, and the tenanted farms are classified as 0. More than 70% of the farms in the UK regions are owner-occupied farms. Around 95% of all farms in the West Midlands are owner-occupied followed by Wales where 91% of farms are owner-occupied. The least percentage of owner-occupied farms were located in North West (73%)

Dummy for regions

Lastly, we have included dummy for regions to show regional differences.

7.4.4. Results

In the previous section, we found that 4.6% of the farms in our sample were technically efficient and that the average efficiency score of dairy farms in the UK regions was 0.72. Once the efficiency scores have been calculated, we can proceed to the second stage. The goal of the second stage is to measure the causes of efficiency by using Tobit regression. Before running any sort of regressions it is important to see whether multicollinearity is present among the independent variables. Multicollinearity means that the independent variables are correlated with each other. It multicollinearity is present in the data, it means that one independent variable can be linearly predicted from others. One method of detecting multicollinearity is the presence of correlation among a number of independent variables. So to test for multicollinearity, correlation coefficient was found for the independent variables used in Tobit regression. The correlation of independent variables is presented in Appendix 7.5. A value of 1 indicates that the variables are positively correlated with each other whereas a value of -1 implies that the variables are negatively correlated with each other. A value of 0 implies that there is no correlation. The closer the value is to 1 or -1, the higher correlation there is, The correlation between all independent variables is between -0.24[35] to 0.71[36]. The correlation coefficient of -0.24 suggests that the variables are weakly negatively correlated with each other. The correlation coefficient of 0.71 implies that the variables are moderately positively correlated with one another. If the correlation coefficient was above 0.75, then that may imply a strong correlation and to solve this problem we would have had to remove one of the highly correlated variables. However, since none of the variables are highly correlated, positively or negatively, to one another, we can conclude that the model may not suffer from the problem of multicollinearity so we can continue to Tobit regression.

We explore relationships between technical efficiency and variable described in the previous section. The results are presented in Table 7.6 where Wales is taken as a base region.

Table 7. 6 : Factors affecting technical efficiency

	Coef.	Std. Err.	P- Value	Sig
AGE	-0.001	0.000	0.001	***
EDU	0.000	0.004	0.899	
INTE	0.097	0.004	0.000	***
LNGVA	-0.337	0.038	0.000	***
LOANS	0.000	0.000	0.000	***
LNLANDCOST	-0.008	0.002	0.000	***
TENURE	0.016	0.007	0.034	**
dregion1	0.050	0.012	0.000	***
dregion2	0.083	0.010	0.000	***
dregion3	0.075	0.010	0.000	***
dregion4	0.053	0.009	0.000	***
dregion5	0.037	0.009	0.000	***
dregion6	0.164	0.014	0.000	***
dregion7	0.177	0.018	0.000	***
dregion8	0.075	0.010	0.000	***
Intercept	4.053	0.365	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

All the variables chosen to explain differences in technical efficiency are significant at the 5% level except for *EDU*. The age of a farmer *(Galagedera, D. U. A. and Silvapulle, P.)* negatively affects the technical efficiency. This relationship can be explained as older farmers are

[35] The correlation coefficient between AGE and EDU. Although minimum correlation is -0.73 between dregion9 and LNGVA, it has been ignored since dregion9 is not included in Tobit regression.
[36] The correlation coefficient between LNLANDCOST and TENURE.

knowledgeable about past production technologies and are more biased towards change (Alfons, W. et al. 1990). Older farmers also tend to be less knowledgeable about environmentally friendly technologies which can reduce their efficiency. On the other hand, younger farmers know more about recent technologies' and are more willing to adopt them which might increase the efficiency of a farm (Hoang, V.-N. and Nguyen, T. T. 2013). There have been mixed results with regards to the age of the farmer and the efficiency of the farm. Similar to our results, Latruffe, L. et al. (2004) and Tipi, T. et al. (2009) also found age had a positive effect on inefficiency while Poudel, K. L. et al. (2015) found a negative effect. It is understandable to obtain a positive effect of age on efficiency when age is taken as a proxy for farming experience.

The educational dummy *(Llanos, E. et al.)* was positive though insignificant implying that a farmer's education does not effect a farm's efficiency. We also included a dummy for intensity *(Interlenghi, S. F. et al.).* A positive sign indicated that higher intensity farms would have a positive effect on efficiency. In this case, the intensity of a farm is a relative measure of its size. Larger farms are considered those which have higher livestock intensity (cows per hectare) and higher milk production per cow and hectare. Larger farms, in this context, were more technically efficient than the smaller farms. Studies that investigated the size of the farm by taking into account the size of the herd found that it had a positive effect on efficiency (Barnes, A. P. 2006) while studies with the area in hectares as a proxy for size of a farm had negative effect on efficiency (Barnes, A. 2008).

LNGVA has been taken to indicate economic activity in that region. *LNGVA* represents the money that has been generated in a region per head through the production of goods and services. *LNGVA* negatively affects technical efficiency. This indicated that the areas where more goods are produced, the efficiency is going to be lower. The regions with high GVA indicate that these regions have been engaging in economic activity which generates more goods and services. Since agriculture in England only contributes 2% to the GVA, it is safe to assume that regions with higher GVA would have lower agricultural activities. These areas would have less reliance on agriculture. Agriculture is generally concentrated in the area with low employment (Brülhart, M. and Traeger, R. 2005) which in turn would make these regions with less GVA. An increase in agricultural concentration simultaneously decreases concentration in manufacturing. Furthermore, the area where the GVA per head is higher, those are those areas would invest less in agriculture as the value added.

The loans *(LOANS)* have had a positive effect on a farm's efficiency. The role of credit in agriculture has been examined in quite a few studies. They all show a positive effect of credit as higher loans availability allows farmers to invest more in the farm making them more efficient. Following credit evaluation and approval approach, banks only lend to those farmers who are low risk as banks evaluate loans according to the borrower's ability of repayment (Davidova, S. and Latruffle, L. 2007). Since farms with higher technical efficiency produce more milk, these farms would be more profitable and be able to obtain a loan from banks. Barnes, A. (2008) also found a positive effect of debt ratio on efficiency in the case of Scottish dairy farms indicating that an increase in capital investments in dairy farms would increase efficiency. However, it needs to be pointed out that farms sometimes borrow based on their historical earnings. An increase in the interest rate would make it difficult for the farmers to repay the loans if they have borrowed heavily hence reducing their efficiency.

LNUAA is the price per hectare of agricultural land. It negatively affects efficiency. The agricultural land categorised into two types; arable land and the land for pasture. The cost of arable land is higher than the cost of land for pasture (ADHB 2018c). So, the areas where land is costly, people will tend to conserve this resource and would want to maximise return on it. Individuals, especially farmers would not want to free up large portions of land for grazing and would want to use land in such a way through which they could increase their profits.

Tenure *(TENURE)* has a positive and a significant effect suggesting that the owner-occupied farms would be more efficient than tenanted farms. This is also expected as the owners of a farm would be willing to put in extra effort to improve the productivity of the farm. Rahman, S. (2003) theorised that if the quality of the land is good then the farmer would be willing to farm it himself but if the quality of the land is bad then he may rent it to the tenants which may affect the efficiency of the farm. Manjunatha, A. V. et al. (2013) added that the tenants might use relatively less quality of inputs like fertiliser and feed due to their poor finances which may drive down the efficiency. Furthermore, the farmer who owns the land would have an easy time acquiring loans as the owned land can serve as collateral (Samson, G. S. et al. 2016).

Lastly, all regional dummies were positive and significant. These locations had a positive effect on farms' technical efficiency. Regions 6 and 7 (East of England and South East) had a larger impact on efficiency than other regions. This can be observed by looking at the average efficiency of regions. We know from Figure 4 that East of England and South East had the highest average efficiency.

7.5. Conclusion and policy implications

In this study, a two-stage methodology was applied to analyse the efficiency of the farms in UK regions. In the first step, using DEA, we estimated technical efficiency of farms with more than 20 dairy cows. Then in the second stage, we used Tobit regression to explain differences in efficiency.

At least 4.2% of the farms in our sample were technically efficient. There were significant differences among regions due to which they have different technical efficiency scores. The dairy farms were concentrated towards the west of the UK, and these regions also had the highest percentage of technically efficient farms. However, the average efficiency was low in these regions. So, it was not necessary that regions that had more technically efficient farms would also have higher average efficiency, overall.

Using Tobit regression, it was found that intensity, loans and ownership of the farm positively influenced their efficiency. The farms with more cows per hectare and higher milk production per hectare and per cow would positively affect efficiency, and the availability of loans would help farmers to invest in new technology hence improving efficiency. We also found that age, cost of land and GVA of the region in which the farm is located negatively influenced efficiency of a farm.

As mentioned before, the GHG emissions were not included in this chapter as a negative output of dairy production. However, we do find a negative relationship between technical efficiency and GHG emissions per unit of milk. Furthermore, we found a positive correlation between the efficiency scores estimated using undesirable DEA in chapter 6 with the efficiency estimates in this chapter implying that the factors influencing efficiency in this chapter will also affect efficiency when taking into account the negative output.

To improve the efficiency of the dairy farms, programmes may be implemented to encourage young individuals to take up dairy farming as a source of employment. Furthermore, mentoring and training plans might motivate young individuals to enter dairy farming. A shift in age demographics would not only affect the efficiency of the farms but also may decrease the level of unemployment of young individuals in the UK. An increase in young individuals willing to enter the agricultural sector might also contribute to possibly reducing rural to urban migration. So, by helping young individuals through training and low-interest rate on loans, they may be able to contribute to the rural economy. We also found that loans positively influence efficiency. The availability of credit on low interest rate may increase a farms' efficiency and might help a farmer to intensify production. Low-interest rates may also make it easier for the farmers to make repayments on the loans.

The intensity of production has also been an influencing factor for the improvement in efficiency. Subsidies may be given to the farmers who want to purchase more animals to increase their herd size. Intensifying dairy production would not only improve efficiency but also reduce GHG emissions per unit of milk

7.6. Appendix

Appendix 7. 1: The characteristics of an average efficient and inefficient farms

		UAA (ha)	Labour Hours (hrs)	Feed (£)	Cows (no.)	Other costs (£)	Milk Produced (hl)	Other income (£)
TE = 1 N=197	Mean	140	7,635	81,326	151	148,966	11,546	174,067
	SD	172	5,896	111,554	160	262,097	12,091	317,343
	Min	19	1,612	1,307	20	255	330	352
	Max	1,278	31,773	531,494	896	2,812,816	57,081	3,289,139
TE <1 N=4308	Mean	140	7,321	87,830	134	135,986	9,288	128,939
	SD	114	3,806	75,007	86	133,810	6,476	138,496
	Min	23	1,782	1,935	20	989	167	445
	Max	1,278	41,340	656,875	774	1,780,178	52,383	2,058,402

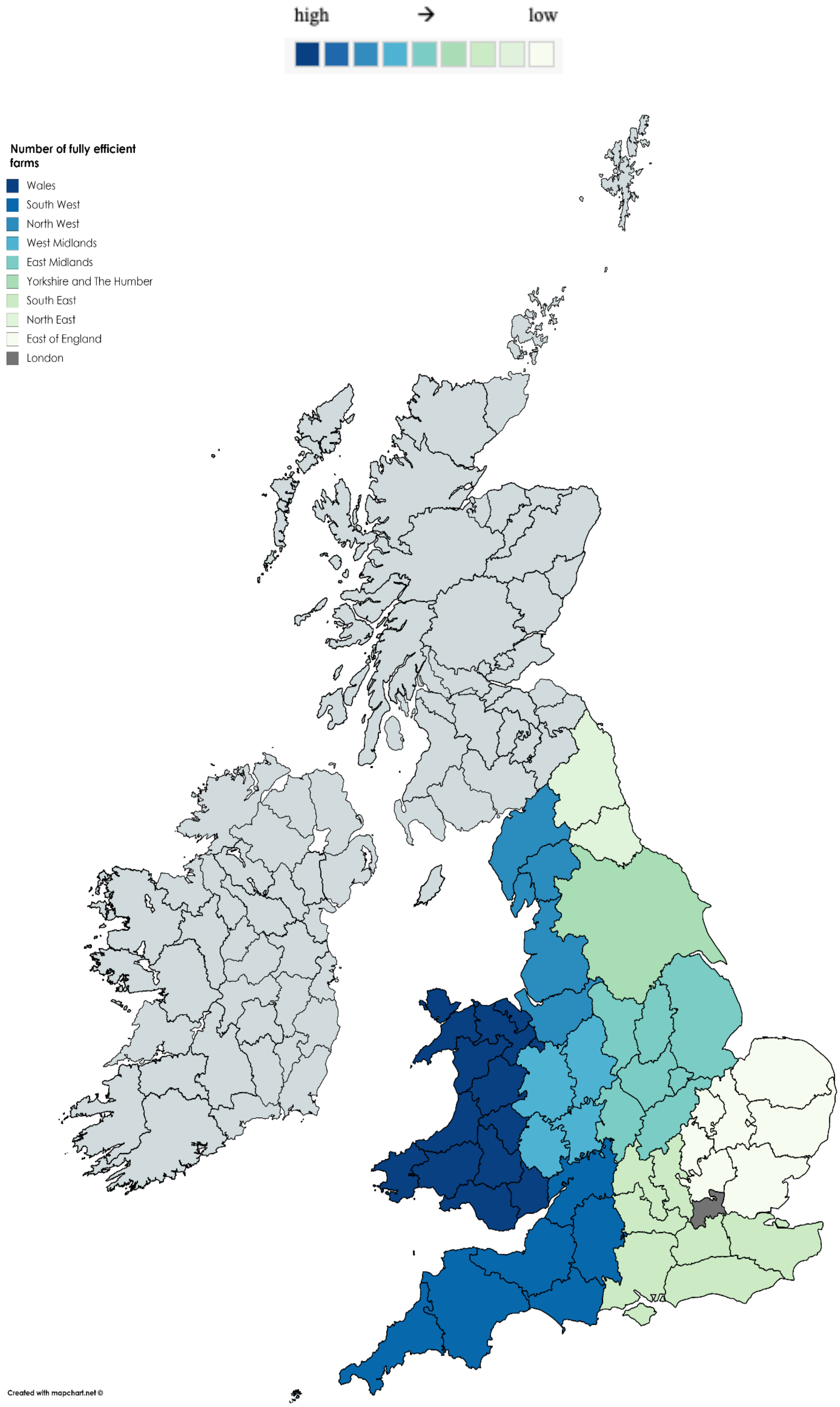
Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

Appendix 7. 2: Descriptive statistics of the regions

	North East	North West	Yorkshire	East Midlands	West Midlands	East of England	South East	South West	Wales	All
UAA (ha)	122	128	126	142	128	215	264	147	114	140
Labour Hours (hrs)	5,200	6,540	6,789	7,871	7,241	10,291	11,258	8,360	5,932	7,335
Feed (£)	67,666	96,386	83,087	83,317	81,235	112,397	113,387	89,228	79,193	87,546
LU (no.)	90	133	121	124	118	148	179	147	132	135
Other costs (£)	110,305	115,805	115,819	125,432	128,857	222,364	254,174	147,816	115,983	136,553
Milk Produced (hl)	6,354	9,534	8,894	9,079	8,260	11,636	13,006	10,102	8,569	9,386
Other income (£)	114,457	100,134	108,576	133,994	135,239	245,546	258,084	137,958	104,354	130,913
No of Farms	123	655	268	357	418	179	240	1,023	1,242	4,505

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

Appendix 7. 3: Number of technically efficient farms



Appendix 7. 4: Mean of farm specific variables

	Mean
AGE	54
EDU	0.46
INTE	0.35
LNGVA	9.86
GVA	19,367
LOANS	137,200
LNLANDCOST	8.35
LANDCOST	7,851
TENURE	0.83

Appendix 7. 5: Correlation of input variables

								dregion								
	AGE	**EDU**	**INTE**	**LNGVA**	**LOANS**	**LNLAND COST**	**TENURE**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
AGE	1															
EDU	-0.24	1														
INTE	-0.04	-0.02	1													
LNGVA	0.00	0.19	-0.06	1												
LOANS	0.03	0.09	0.05	0.13	1											
LNLANDCOST	0.13	-0.05	0.13	0.00	0.19	1										
TENURE	0.15	-0.06	0.00	-0.08	0.15	0.71	1									
dregion1	-0.01	0.04	-0.05	-0.13	-0.07	-0.04	-0.06	1								
dregion2	-0.08	0.04	0.04	0.18	-0.10	-0.14	-0.11	-0.07	1							
dregion3	-0.06	-0.06	-0.02	-0.02	-0.02	0.03	0.00	-0.04	-0.10	1						
dregion4	0.00	0.04	-0.06	-0.03	-0.05	-0.08	-0.07	-0.05	-0.12	-0.07	1					
dregion5	0.03	0.05	0.01	-0.01	0.03	0.11	0.10	-0.05	-0.13	-0.08	-0.09	1				
dregion6	0.03	0.10	-0.08	0.20	0.03	-0.01	0.03	-0.03	-0.08	-0.05	-0.06	-0.07	1			
dregion7	0.07	0.07	-0.08	0.51	0.16	-0.02	-0.03	-0.04	-0.10	-0.06	-0.07	-0.08	-0.05	1		
dregion8	-0.09	0.04	0.00	0.36	0.06	0.05	-0.03	-0.09	-0.22	-0.14	-0.16	-0.17	-0.11	-0.13	1	
dregion9	0.11	-0.19	0.10	-0.73	-0.02	0.05	0.12	-0.10	-0.25	-0.16	-0.18	-0.20	-0.13	-0.15	-0.33	1

8. ASSESSING THE CONVERGENCE IN COST EFFICIENCY OF UK REGIONS

8.1. Introduction

This chapter aims to assess convergence in the cost efficiency of dairy farms in the UK from 2006 to 2014. The current trend in the dairy sector in the UK shows that the number of dairy producers is falling (Chapter 3.3). The decision to leave in dairy farming has been linked to high input costs (DairyCo 2013). It has become increasingly important to determine the optimal quantity of inputs required based on minimising their costs.

We need to ask if there is an improvement in the cost efficiency of regions over the years. Are the regions with relatively lower cost efficiency increasing their efficiency more rapidly than the regions with high cost efficiency. Would the lower cost efficient regions eventually catch up or would the differences in the cost efficiency among the regions grow wider over time?

The growth theory states that the per capita income of different regions would converge to their steady state equilibrium in the long run. Borrowing from the growth theory, the methodology used to test for convergence to the steady state is the β-convergence and σ-convergence. The β-convergence occurs when a low per capita income region grows faster than the region with high per capita income. The σ-convergence occurs when the standard deviation of per capita gross domestic product (GDP) falls over time. The concept of convergence focuses on whether the poor countries can catch-up to the rich countries.

Rather than focusing on growth in income per capita of the region, we would assess β- and σ-convergence of cost efficiency among the regions in the UK. This chapter would aim to test whether the regions with lower cost efficiency would eventually catch-up to the regions with higher cost efficiency.

Specific objectives of this chapter are: to estimate cost efficiency [37] of dairy farms in the UK; to assess the differences in cost efficient and inefficient farms; to determine the potential of reduction in inputs and increase in outputs of dairy production and lastly to assess the convergence in cost efficiency.

[37] Revenue efficiency of the farms is also estimated with majority of the results presented in the Appendix of this chapter.

The cost efficiency has been estimated using Data Envelopment Analysis (DEA). The cost efficiency provided us with the optimal targets that the farms could mimic to reduce their production costs while producing the same level of output. The concept of β-convergence and σ-convergence is used to examine the properties of the convergence of cost efficiency.

This chapter has been organised as follows. Section 2 describes the framework used in estimating cost efficiency and reviews the concept of convergence. Section 3 presents a description of the data used in the estimation of cost efficiency. Section 4 presents and discusses the results of cost efficiency and the convergence in the cost efficiency of regions. Section 5 of this chapter describes the factors that can help to improve a farm's profitability and lastly section 6 concludes the chapter.

8.2. Methodology

This section outlines the theoretical framework used for estimating cost and revenue efficiency. This section also outlines the concept of convergence in growth literature.

8.2.1. <u>Cost Efficiency</u>

Cost Efficiency can be defined as "the ratio of minimum production costs observed in the sample to actual production cost of the DMU evaluated" (Avkiran, N., K 2006). The concept of cost efficiency has been discussed in detail in Chapter 4.

The cost efficiency is estimated using the model presented by Zhu, J. (2009a). It follows as

$$\left.\begin{aligned}&\min \textstyle\sum_{i=1}^{m} p_i^o \tilde{x}_{io}\\ \text{St:}\quad &\textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \le \tilde{x}_{io}\\ &\textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}\\ &\lambda_j, \tilde{x}_{io} \ge 0\end{aligned}\right\} \quad (8.1)$$

Where *i=1,2,….,m, r=1,2,….,s* and p_i^o is the unit price of input i of DMU_0.

Where m are input observations, i refers to m^{th} input. Price data can vary from one DMU to another. The above model is a constant return to scale (CRS) model. To convert this model to suit variable returns to scale (VRS), we need to add another equation:

$$\sum_{j=1}^{n} \lambda_j = 1 \quad (8.2)$$

This condition allows the software to match DMUs against other DMUs of similar size. The cost efficiency of DMU_0 (CRS or VRS) can be defined as:

$$\frac{\sum_{i=1}^{m} p_i^o \tilde{x}_{io}^*}{\sum_{i=1}^{m} p_i^o x_{io}} \tag{8.3}$$

A DMU is considered as allocative efficient if it generates output by using minimum inputs which have minimal costs (Avkiran, N., K 2006). Allocative efficiency is calculated as a ratio of cost efficiency to technical efficiency. Farms with an allocative efficiency score equal to 1 are using inputs appropriately for cost minimisation. To account for variation in input prices that may affect a farms' cost efficiency over the sample period, the separate frontier is estimated for every year (Desli, E. 2009).

The methodology used to estimate revenue efficiency is given in Appendix 8.1.

8.2.2. Convergence

The convergence is of two types: β-convergence and σ-convergence. The convergence of β-type considers if the growth in productivity exhibits a negative correlation with its current level of productivity. So, in other words, β-convergence tests if the firms with the lower level of productivity have faster growth rates than the firms with the higher initial level of productivity. The σ-type convergence considers the dispersion of productivity level decreased over time (Fung, M. K. 2006).

The β-convergence can be either absolute or conditional. In absolute β-convergence, the output is regressed on its lagged value to test for absolute convergence. In absolute convergence, each firm moves towards the same steady-state productivity. So, the absolute convergence assumes that the only difference across the firms is their initial level of productivity. In conditional convergence, the output value is regressed on its lagged value and other conditional variables to test for conditional convergence. Thus, in conditional convergence, each firm has its own steady-state productivity which it converges to.

The widely cited study on convergence is by Barro, R. J. and Sala-i-Martin, X. (1990); Barro, R. J. and Sala-i-Martin, X. (1992) who used the concept of β-convergence and σ-convergence to estimate whether the poor countries tend to grow faster than the rich countries.

A variety of studies based on Barro, R. J. and Sala-i-Martin, X. (1992)have examined the convergence of bank efficiency and productivity. Daley, J. et al. (2013) tested for β-convergence and σ-convergence of cost efficiency in Jamaican banks. Fung, M. K. (2006) tested for β-convergence and σ-convergence of technical and scale efficiency of the bank holding companies in the US. Matthews, K. and Zhang, N. (2010) measured Chinese banks' productivity and estimated the convergence of productivity. Matousek, R. et al. (2015) test for convergence in bank efficiency to test for bank integration in the Eurozone. A variety of studies exists that estimate convergence of GDP per capita and banking efficiency; however, less emphasis has been placed on convergence in the agriculture sector.

Martin, W. and Mitra, D. (1999) estimated productivity growth and convergence in agriculture and manufacturing using the data from 50 countries. They first estimated the total Factor Productivity of a country's agriculture and manufacturing and then tested for TFP's convergence. They found that the agriculture sector had higher TFP growth and faster speed of convergence than the manufacturing sector. De Siano, R. and D'Uva, M. (2006) investigated club convergence (Baumol, W. J. 1986)[38] in European regions to determine if the region's per capita income converges to the average of its group. Four region groups were formed based on their specific characteristics. The groups characterised by high average GDP growth rate and strong specialisation in agriculture showed weak convergence to the group's average. The groups that consisted of regions with the lowest average growth rate of GDP had strong convergence to the group's average.

Similarly, Alexiadis, S. (2012) also tested for regional convergence of gross value added (GVA) per worker in agriculture of EU-28. Using OLS to test for β-convergence in EU-25 regions, he found signs of absolute convergence over the period 1995 to 2004. He further included tests for club convergence (Baumol, W. J. 1986) and found that the rich countries had the lower rate of growth whereas the poor countries had higher growth rate. The countries that did not belong to a rather rich or poor countries club had a slower rate of convergence. He concluded that the regional convergence is not uniform in Europe especially in the case of agriculture.

[38] The poor countries would converge towards one another and create a convergence club and the rich countries would converge to one another and create another convergence club. So, the poor and the rich economies would converge within their own club and there would be no convergence from one group to another.

Baumol, W. J. (1986) contributed largely to the concept of convergence by statistically testing the hypothesis that poor economies will catch-up with the rich economies. He found a negative relationship between the initial levels and growth rate of per capita output. He presented the following equations

$$y_{i,t} - y_{i,t-1} = a + by_{i,t-1} + \varepsilon_i \tag{8.4}$$

Where:

$y_{i,t-1}$: The natural logarithm of output at initial time for the i^{th} region

$y_{i,t}$: The natural logarithm of output at current time for the i^{th} region

a : Constant term

b : The convergence coefficient

ε : Random error term

The intercept, a is the steady-state level of the output and by assuming that coefficient is the same across all regions would imply that the steady state is the same for all the regions (Desli, E. 2009).

The condition of convergence requires that the first difference is negative as shown by:

$$\frac{\partial(y_{i,t} - y_{i,t-1})}{\partial y_{i,t}} = b < 0 \tag{8.5}$$

So, the regions with relatively low initial output would grow faster than the regions with a relatively high initial output indicating that poor economies would grow faster than the rich economies.

σ-convergence measures the dispersion in income and captures how quickly each country's or region's income level is converging to the average level of the country's group (Parikh, A. and Shibata, M. 2004). So, in this study σ-convergence measures how quick a region's cost efficiency is converging to the average level of the country's average.

Following Parikh, A. and Shibata, M. (2004), the σ-convergence is estimated by:

$$E_{i,t} - E_{i,t-1} = \rho + \phi E_{i,t-1} + \varepsilon_{i,t} \tag{8.6}$$

Where $E_{i,t} = y_{i,t} - \bar{y_t}$ and $E_{i,t-1} = y_{i-1,t} - \overline{y_{t-1}}$. $\bar{y_t}$ is the average efficiency score at time t. A negative value of ϕ would imply σ-convergence and would represent the rate of convergence of $y_{i,t}$ to $\bar{y_t}$. The larger the absolute value of ϕ, the faster is the rate of convergence.

8.3. Inputs and outputs price data

The input and output variables data is collected from the Farm Business Survey (FBS). Inputs used in the study are the labour hours, animal feed and the number of dairy cows on the farm. The output variables are the quantity of milk produced on the farm.

An important input variable of Utilised Agricultural Area (UAA) has been omitted when estimating cost and revenue efficiency. The UAA has been ignored as an input variable as farm area cannot be changed in the short run (Wettemann, P. J. C. and Latacz-Lohmann, U. 2017). The UAA in the UK has remained relatively the same over the years with some slight changes in the average farm size in Wales and England over the sample period (Chapter 5.2). In DEA, the variables that cannot be changed in the short term are known as non-discretionary variables. Although the land is an important input for DEA, we are focusing on reducing variable costs. Thus, the effects of land on cost efficiency have been ignored and cost efficiency has been estimated using the variable that the farmers can more easily change in the short term. Table 8.1 shows the variable cost data for inputs and output prices.

Table 8. 1: Inputs and Outputs

		2006	2008	2010	2012	2014
Labour hours (£ per hour)	**Mean**	9.3	9.5	9.7	9.5	9.5
	SD	1.5	1.4	1.5	1.4	1.5
Feed (£ per tonne)	**Mean**	166	215	218	250	237
	SD	1.3	12.8	7.4	9.8	12.6
Cows (£ per unit)	**Mean**	751	1,010	1,082	1,102	1,067
	SD	152	324	240	261	200
Milk Income (£ per hl)	**Mean**	23.7	29.6	27.6	29.6	31.6
	SD	3.5	5.1	3.6	2.7	3.1
No of obs.		885	921	939	900	860

Source: DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The input variable of labour hours is given as the wage rate of that year. The wages of farmers over the years have remained relatively stagnant, ranging from £9.30 per hour to £9.70 per hour. The input variable of feed is given in £ value per tonne. The FBS only provides information on the total cost of the feed purchased by a farm. They do not provide information on the quantity of the feed purchased. To estimate cost efficiency, we need to know their input and output quantities as well as prices. To determine the quantity of feed, we have used the data provided by ADHB for feed prices and have calculated the quantity of feed purchased accordingly. The cost of one tonne of feed ranged from £166 per tonne to £250 per tonne. So, there has been a 43% increase in the cost of feed over the period of 10 years.

The input variable of cows is denoted as £ per cow. The input values for this variable has been directly taken from the FBS. The average cost of a dairy cow in 2006 was £751 and has increased to £1,067 by 2014. So, there has been a 42% increase in the cost of the cow over the course of 10 years (in money terms). The income generated from the sale of one hectolitre of milk ranged from £23.7 to £31.6 from 2006 to 2014. So, the income from one hectolitre of milk increased by 33% from 2006 to 2015.

All prices taken are farm specific prices (except for feed), so they would show that efficiency scores are affected by different procurement practices (Wettemann, P. J. C. and Latacz-Lohmann, U. 2017). The total cost production and total income per farm and hectolitre are presented in Table 8.2.

Table 8. 2: Total production costs and income per farm and per hectolitre of milk (2006-2014)

	2006	2008	2010	2012	2014
Total Cost per farm (£)	215,909	260,163	322,991	331,686	345,871
Total income per farm (£)	195,108	268,118	266,899	294,859	335,808
Price/cost ratio (Total)	90%	103%	83%	89%	97%
Total Cost of milk production (£/hl)	30.20	32.75	39.37	36.89	36.53
Milk price per hl (£ per hl)	23.68	29.63	27.61	29.57	31.58

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The average costs per farm include the cost of labour wages, the purchase of feed and the dairy animals. The average cost of a farm in the year 2006 was £215,909 which rose 60% over the course of 10 years. The average income per farm only includes income generated from the sales of milk. So, it would not include any subsidies or grants received by the farmer. The average income per farm in the year 2006 was £195,108 and rose to £335,808 by 2014. So, the income per farm increased 72% over ten years.

Then the price/cost ratio was calculated by dividing the total cost of production by the total income. Price/cost ratio was calculated to identify if the farm income could cover the costs of production. The price/cost ratio indicated that the total income covered almost 83% (or higher) of the costs. Only in the year 2008, the price ratio was above 100% indicating that the higher income was generated than the cost of production.

The cost of producing one hectolitre of milk has increased by 21% from 2006 to 2014. In the year 2006, the cost of producing one hectolitre milk was £30.20 which increased to £36.53 by 2014. In 2006, the price of milk per hectolitre was almost £24 which has increased to £32 per hectolitre by 2014.

Over the course of 10 years, the total costs per hectolitre of milk produced per farm have risen 60% while the total income generated per farm per hectolitre of milk has risen 72%. Approximately 95% of the farms in the sample are classified as specialised dairy farms whose output from dairy cows constitutes 67% of the total farm output per head of livestock. If the farms are specialised dairy farms, the income they generate from sales of milk would barely cover their costs. Under such conditions, it is becoming increasingly difficult for the farmers to continue with dairy production. Many farmers have left dairy production which can be observed by the declining producer numbers in Wales and England.

The question then arises: Why are some producers continuing with dairy production despite it being unprofitable? The answer to this question lies in the hidden benefits that may not be translated into monetary terms. The farmers sometimes do not expect to receive the same return that they would get if they chose some alternate form of employment. This is because the non-monetary benefits that they receive are much higher than they would have been able to get otherwise. These non-monetary benefits include housing, independence, proximity to work and enjoyment of work. Housing is particularly important to small tenanted farmers who are housed on the farm. Housing on the farm may be far better than they would have been able to afford alternative employment.

Many farmers value their independence and they continue to engage in dairy farming as it gives them the freedom to be their own boss even though it might not be profitable. Proximity to work is another important factor as to why farmers continue with dairy farming. Especially in rural areas, people need to commute longer distances to find work and the individuals maybe are required to get a private car as the public transportation may not reach far places (DEFRA 2013).

8.4. Results

With rising costs of inputs, it has become increasingly important for farmers to evaluate their farming practices to minimise the cost of production. Moreover, it is becoming increasingly important for the farmers to use their inputs effectively to produce maximum outputs that can maximise revenue. Using the DEA Frontier, the cost and revenue efficiency of farms was estimated and the results of cost efficiency are presented in this section, and the results of revenue efficiency are presented in Appendix 8.1.

8.4.1. Cost Efficiency[39]

The cost efficiency of farms was estimated, and the differences between the cost efficient and inefficient farms were examined in detail. Cost Efficiency can be defined as "the ratio of minimum production costs observed in the sample to the actual production cost of the DMU evaluated" (Avkiran, N., K 2006). Cost efficiency is also known as "economic efficiency" or "overall efficiency". It can be expressed as a product of input-oriented technical efficiency and allocative efficiency.

$$Cost\ Efficiency = Technical\ Efficiency \text{ x } Allocative\ Efficiency$$

Technical efficiency is the ratio of actual productivity and the best practice frontier (Wossink, A. and Denaux, Z. S. 2006). Farrell, M. J. (1957) defined technical efficiency as the relative distance to the frontier while keeping output constant but reducing the use of inputs proportionally to become efficient. Efficiency is then measured by using actual firm data that generates a frontier. The firms that create or lie on the frontier are considered as efficient firms. The firms that lie above or below the frontier are considered as inefficient firms. The existence

[39] The revenue efficiency of the farms is also estimated using DEA and the results are presented in the appendix. The farms that were revenue efficient were cost efficient as well though there were a higher number of farms that were revenue efficient implying that the farms. Approximately 4-5% of the farms in sample years were revenue efficient with and the remaining inefficient farms could potentially increase their revenue by 24-36% while using the same level of inputs.

of inefficiencies of a firm offers the firm an opportunity to reduce their inputs to produce the same level of outputs.

Allocative efficiency is the ratio of cost efficiency and technical efficiency. Allocative efficiency is also known as price efficiency. It shows the relative cost reduction of a firm when it moves from a frontier point to a point where the input costs are minimised given the output level (Førsund, F. R. 2018). Farms with allocative efficiency score equal to 1 use input combination to minimise costs. A score of less than 1 indicates that the input combination is not cost minimising.

A farm is going to be technically efficient when it produces output using minimum inputs. A farm is going to be cost efficient when it produces output at minimum cost. A farm is going to be allocative efficient if it produces output while using minimum inputs to minimise the cost of production.

All farms that were cost efficient were allocative efficient, but not all farms that were cost efficient were technically efficient. The number of cost, technical and allocative efficient farms is presented in Table 8.3 and the average efficiency scores for cost, technical and allocative inefficient farms is presented in Table 8.4.

Table 8. 3: Number of Cost, Technical and Allocative efficient farms

	2006	2008	2010	2012	2014
Cost	7	9	7	8	7
Technical	34	34	44	34	37
Allocative	7	9	7	8	7
Total	885	921	939	900	860

A more significant portion of farms was technically efficient compared to cost efficient implying that majority of the farms were producing output given minimum input while fewer farms were producing output at the minimum cost of production given the input price level.

In 2006, 0.8% of farms were cost and allocative efficient while 4% of the farms were technically efficient. So, 0.8% of the farms were using their inputs in the proportion that would minimise their costs while 4% of the farms were producing output while using minimum inputs. Average technical efficiency score of farms was 68% indicating that the farms could reduce their inputs by 32% and produce the same level of output. The farms in this year could potentially reduce their costs by 39% to produce the same output. The average allocative efficiency score was 90% implying that farms were not using their inputs in a cost minimising way given the input prices.

In the year 2008, 1% of the farms were cost and allocative efficient while 4% of the farms were technically efficient. The average cost, allocative and technical efficiency score was 59%, 86% and 75%, respectively. The farms could reduce their costs by 41% and reduce their inputs by 31% and produce the same level of output. The average allocative efficiency implied that they were not using their inputs in the cost minimising level given the input prices and could reduce their cost by 14% to produce the same level of output.

In the year 2010, 0.8% of farms were cost and allocative efficient while 5% of the farms were technically efficient. The average technical efficiency score was 78% implying that the farms could reduce input use by 22% for them to become technically efficient. Cost efficiency score, on an average, was 69% implying that farms could potentially reduce their cost by 31% and still produce the same level of output. Average allocative efficiency score for farms was 88%.

In the year 2012, 0.9% of the farm were cost and allocative efficient while 4% of the farms were technically efficient. The average cost efficiency score was 61% implying that they could reduce their costs by almost 39% and produce the same level of output. The farms could also reduce their input use by almost 29% to produce the same level of output. The 99% of farms who were allocative inefficient were not using their inputs in cost minimising levels given the input prices and they could reduce costs by 14% while minimising inputs to achieve the same level of output.

Table 8. 4: Average Cost, Technical and Allocative Efficiency Score of inefficient farms

	Cost Efficiency	Technical Efficiency	Allocative Efficiency
2006	0.61	0.68	0.90
2008	0.59	0.69	0.86
2010	0.69	0.78	0.88
2012	0.61	0.71	0.86
2014	0.72	0.78	0.92

In year 2014, 0.8% of the farms in the sample were cost and allocative efficient while 4% of the farms were technical efficient. The average technical efficiency score was 78% implying that the farms could become technically efficient by reducing their inputs by 22% and produce the same level of output. The farms, on an average, could reduce their costs by 28% and produce the same output level. A higher allocative efficiency score in the year 2014 implied that most farms in this year were using input mix that was close to the input mix that minimised costs.

Thus, approximately 1% of the farms in the sample period were cost and allocative efficient whereas 4-5% of the farms were technically efficient. The farms could reduce their inputs by 22-32% to become technically efficient. A reduction in the use of inputs by 22-32% would not lead to a reduction in the outputs produced. The farms in the sample could potentially reduce their costs up to 28-41% and still produce the same level of outputs.

The allocative efficiency score, for the sample period, ranged from 86-92% from 2006-2014. This suggests that if the farms reduce their input usage by 22-32% (if they become technically efficient) to produce the same level of output, then they can potentially minimise the cost of production and save approximately, 8-14% of the total costs.

A breakdown of cost efficiency scores over the years is presented in Table 8.5.

Table 8. 5: Farm frequency according to cost efficiency scores

	2006	2008	2010	2012	2014
< 0.1	0	0	0	0	0
0.1 - < 0.2	0	2	0	1	0
0.2 - < 0.3	3	4	2	1	3
0.3 - < 0.4	36	65	13	18	6
0.4 - < 0.5	146	200	56	100	30
0.5 - < 0.6	249	265	159	295	118
0.6 - < 0.7	256	184	253	313	219
0.7 - < 0.8	127	115	264	133	257
0.8 - < 0.9	46	62	133	26	187
0.9 - < 1	15	15	52	5	33
1	7	9	7	8	7

Approximately 1% of farms in the sample are cost efficient, having cost efficiency score equal to 1. In 2006, 7 farms were cost efficient so they were using their inputs in a combination that produced output at a minimum cost while the remaining 878 farms were inefficient. The remaining cost inefficient farms could reduce their costs and still produce at the same output level.

None of the farms in the year 2006 had a cost efficiency score below 0.2. The majority of the farms in this year had a cost efficiency score between 0.6 and 0.7. Almost 29% of the farms could reduce their costs by 30-40% and produce at the same output level. In the year 2008, 2 farms had an efficiency score below 0.2. Approximately, 29% of the farms in 2008 could reduce their cost by more than 50% while 49% of the farms could potentially reduce their costs by 30-50% and still produce at the same output level.

In the 2010 and 2014, none of the farms in the sample had a cost efficiency score of less than 0.2. In the year 2010, 2012, and 2014, only 8%, 13% and 5% of the farms could potentially improve their cost efficiency and reduce their production cost by more than 50% and still produce the same level of output, respectively.

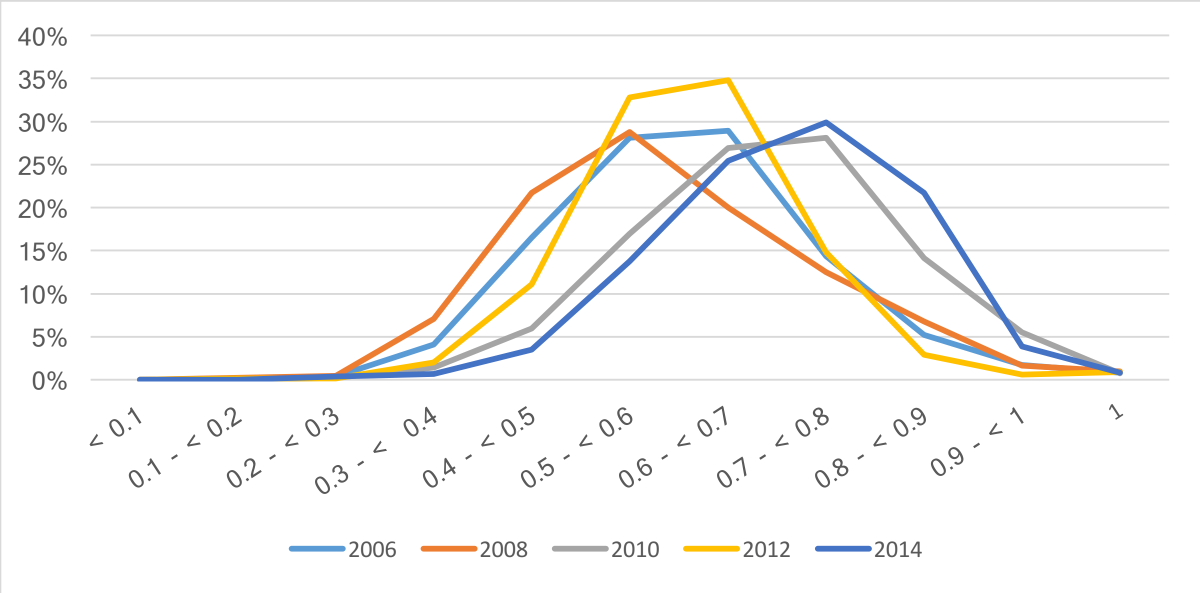
In the year 2012, approximately 35% of the farms could reduce their cost by 30-40% and still produce at the same level of output and 15% of farms could potentially reduce the cost of production by 20-30% and produce the same level of output.

In the year 2014, approximately 1% of the farms in the sample were cost efficient and only 5% of the farms could reduce their cost by more than 50%. The largest number of farms belonged to the efficiency score bracket of 0.7 - < 0.8 implying that 30% of farms could become cost efficient by reducing their cost of production by 20-30%.

The farm data comprises of an unbalanced panel where the number of farms varies over the years as new farms enter the survey and old farms exit the survey. An unbalanced panel coupled with the properties of DEA does not allow us to have a year to year comparison. The DEA is a relative measure of efficiency which estimates efficiency only according to the DMUs present in the data. So, it is possible that a DMU that accurately reflects the practices is not included in the data and hence cannot influence the frontier.

However, by looking at Table 8.5, we can see that the cost efficiency of firms is increasing over the years. We can then plot the percentage of farms in an efficiency score bracket which is shown in Figure 8.1.

Figure 8. 1: Percentage of farms in an efficiency score bracket



We can see that the over the years, the percentage of farms in the higher efficiency score brackets is skewed towards the right. As the years pass, the percentage of farms being categorised into higher efficiency score groups are increasing. A question then arises is there any convergence of efficiency? In Chapter 8.5.2 we use the concept of β and σ-convergence to determine if there is a convergence in cost efficiency.

Difference between cost efficient and inefficient farms

We need to understand and evaluate the difference between the cost efficient and inefficient farms to determine factors that could contribute to reducing farm's cost. The results are presented in Table 8.6.

The Mann-Whitney U test was used to evaluate the differences among the two groups, cost efficient and inefficient farms. Cost efficient farms had an efficiency score equal to 1. These farms were also allocative and technically efficient which implied that these farms were using the minimum quantity of inputs to produce output at a minimum production costs thus these farms may act as benchmarks that the inefficient farms need to mimic to produce the same output at minimum cost while using the minimum quantity of inputs.

Table 8. 6: Characteristics of cost efficient and inefficient farms

	CE <1		CE = 1		P-value	Sig.
	Mean	**SD**	**Mean**	**SD**		
UAA (ha/farm)	140	117	148	132	0.406	
Cows (cows/farm)	134	86	252	270	0.751	
Labour Hours (lh/farm)	7,316	3,860	9,550	8,248	0.970	
Feed (t/farm)	398	334	664	743	0.715	
Milk Produced (hl/farm)	9,292	6,572	20,487	18,492	0.007	***
Total production cost (£/farm)	293,562	190,002	489,528	454,445	0.242	
Total income (£/farm)	269,195	204,712	576,269	536,860	0.013	**
Milk yield (hl/cow)	67	16	98	56	0.000	***
Stocking Intensity (cows/ha)	1.19	0.63	1.51	0.67	0.001	***
Labour hours per cow (lh/cow)	64	34	69	64	0.145	
Feed per cow (t/cow)	2.93	1.42	2.77	2.54	0.058	*
Production cost per cow(£/cow)	2,243	610	2,599	1,991	0.129	
Total income per cow (£/cow)	1,918	558	2,707	1,628	0.000	***
Output input ratio (£)	0.88	0.25	1.1	0.25	0.000	***
GHG per hectolitre of milk (CO_2 eq/hl)	79	43	65	29	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

The average area of cost inefficient farms was 140 hectares whereas the efficient farms were 148 hectares. The difference in area between the two farm types was not statistically significant. The minimum farm size of a cost efficient farm was 20 hectares and the maximum size was 472 hectares so cost efficient farms could be found in any size of a farm. The herd size of cost efficient farms consisted of 252 cows whereas the herd size in cost inefficient farms was 134 cows. The cost efficient farms had 88% more cows than the inefficient farms. The average herd size of cost efficient farms ranged from 20 cows to 896 cows. However, the differences in herd size in cost efficient and inefficient farms was not statistically significant.

The cost efficient farms had higher labour hours per farm than the cost inefficient farms but the differences were not statistically significant. No significant differences were found between the quantity of feed purchased by cost efficient and inefficient farms. This suggests that both farm types purchased the similar quantity of feed

The cost efficient farms produced more milk per farm. The cost efficient farms produced 20,487 hl of milk while inefficient farms produced 9,292 hl of milk. The difference in milk production per farms by between two farms types was statistically significant despite no significant differences being found in the herd size.

Since the milk production per farm was significantly higher in the cost efficient farm, these farms then also generated higher total income per farm. The total income generated at a cost efficient far was £576,000 whereas the total income generated on a cost inefficient farm was equal to £269,000. The total production cost higher for cost efficient farms but the differences between the two farm types were not statistically significant.

The milk yield per cow was higher for cost efficient farms and the difference between the two farm types was statistically significant. The cows in cost efficient farms produced 46% more milk than the cows in cost inefficient farms.

The stocking intensity of the farm was measured as the number of dairy cows per hectares. The stocking intensity was higher in cost efficient farms and the difference was statistically significant. The cost efficient farms contained 2 cows per hectare whereas inefficient farms contained only one cow per hectare which shows that cost efficient farms were more intensive.

The labour hours per cow were 8% higher for cost efficient farms compared to inefficient farms but the differences were not statistically significant. The cost efficient farms purchased 2.77 tonnes of feed per cow while the cost inefficient farms purchased 2.93 tonnes of feed per cow. The feed per cow was 5% lower in cost efficient farms and the differences between the two groups were statistically significant at a 10% significance level.

The differences among cost efficient and inefficient farms were not statistically significant for the variables total production costs per cow. However, the cost efficient farms produced generated 41% higher income per cow than the cost inefficient farm and the difference between milk productions per cow was statistically significant. Although the total production costs per farm and per cow were not statistically significant, the output to input ratio was statistically significant. The cost efficient farms had an output-input ratio higher than one indicating that they could cover their costs by the income generated on the farm. It was also found that the cost efficient farms produced significantly less GHG emissions per hectolitre of milk produced compared to the cost inefficient farms. The cost efficient farms produced 65 kg CO_2 equivalent emissions per hectolitre of milk whereas the cost inefficient farms produced 79 kg CO_2 equivalent emissions per hectolitre of milk.

The cost efficient and inefficient farms had similar area and herd size per farm and they faced similar production costs per farm and per cow. The other inputs of production like labour hours and the quantity of feed purchased by these farms were also similar. However, the cost efficient farms produced 120% higher output in terms of milk production per farm than the cost inefficient farms. Due to the higher output by the cost efficient farms, they also generated higher income per farm. The higher milk production per farm was a result of higher milk production per cow in cost efficient farms. Generally, higher milk production by a cow is due to differences in genetics, feeding practices and lactation cycles. So, the cost efficient farms perhaps were using a better quality of feed which enhanced the milk production by an animal. The cost efficient farms also had higher stocking intensity. A higher stocking intensity combined with significantly higher milk production per cow allowed us to classify the cost efficient farms as intensive farms according to the characteristics of intensive farms defined in Chapter 6.3.3. From the results of Chapter 6.3, we found that the intensive farms also produced less GHG emission per hectolitre of milk. This is also true for the cost efficient farms. We found that the cost efficient farms produced less GHG emission per hectolitre of milk produced than the cost inefficient farms. So, the cost efficient farms could be classified as intensive farms.

Optimal targets for Cost Efficiency

The cost efficiency was estimated in the previous section using DEA and found that 99% of the farms in the sample were cost inefficient. These farms could potentially reduce their cost, on an average, anywhere between 28 – 41%. To ensure cost efficiency, there is a need for the reduction of inputs. The DEA provides us with the optimal targets for each farm by projecting inefficient farms onto the frontier. These input targets identify the reduction in inputs required for production at a minimum cost.

The percentage reduction in input costs that could potentially be achieved if the inefficient farms follow the practices of the efficient farm is presented in Table 8.7.

Table 8. 7: Percentage reduction in input quantities (2006-2014)

	Labour Hours	Feed	Cows
2006	-16%	-49%	-42%
2008	-30%	-55%	-29%
2010	-38%	-34%	-17%
2012	-21%	-39%	-39%
2014	-48%	-16%	-21%

In the year 2006, cost efficiency score for the cost inefficient farms was 61% implying that these farms could reduce their production costs by 39% and produce at the same level of output. This cost reduction was mainly due to a 49% reduction in the quantity of feed. Furthermore, a 42% reduction in the number of cows and a 16% reduction in the labour hours was needed for these farms to become cost efficient.

In the year 2008, 1% of the farms were cost efficient. Like in 2006, cost inefficiency was primarily due to the large quantities of feed purchased by these farms. For these farms to become cost efficient, they required a 55% reduction in the quantity of feed purchased. These farms also required a 29% reduction in the number of cows and a 30% reduction in the labour hours for these farms to become cost efficient. By reducing the above quantities, these farms could become cost efficient and reduce their costs of production by 41% while producing the same level of output

In the year 2010, the farms could potentially reduce their costs of production by 31% and still produce the same level of output. A 31% reduction in costs could be achieved by potentially reducing the quantity of feed purchased by a farm by 34%, labour hours by 38% and the number of cows by 17%.

In the year 2012, the farms could reduce their costs by 39% and produce the same level of output. This reduction in costs was mainly due to a 39% reduction in the quantity of feed purchased and the number of cows on the farm. This was followed by a 21% reduction in labour hours.

Lastly, in the year 2014, the farms could reduce their costs by 28%. A 16% reduction in the quantity of the feed led to a similar reduction in the cost of feed and other costs. These farms could also reduce labour hours by 48% and cow numbers by 21% to become cost efficient and produce the same level of output at minimum cost. The primary source of cost inefficiency in dairy farms was the large quantity of feed purchased by inefficient farms followed by the excessive use of labour.

8.4.2. Robustness of Cost Efficiency

The robustness of cost efficiency was examined as the number of cost efficient farms were relatively fewer compared to the efficient farms in the previous chapters. Only 1% of the farms in the sample years were cost efficient and 4% of the farms were technically efficient. In the previous chapters, we found that approximately 13 to 16% of the farms were technically efficient. The robustness was tested for cost efficiency to make sure that the efficient farms were not pulling the frontier away from the farms that could potentially be efficient as a number of farms had efficiency score between 0.8 and 1. Although comparing the efficiency scores obtained in these two chapters (chapter 6 and chapter 8) is not possible as the number of inputs and outputs are different however according to Zhu, J. (2009b), improvement in technical efficiency can be achieved by decreasing the number of inputs. We see that efficiency has decreased when the number of inputs are reduced. This prompted us to test for robustness of efficiency scores.

The robustness of DEA models is checked through a variety of methods like comparing the efficiency scores obtained from SFA with the efficiency score obtained from DEA (Gong, B.-H. and Sickles, R. C. 1992), by analysing the effect of omitting or including variables in the DEA models (Pedraja-Chaparro, F. et al. 1999; Galagedera, D. U. A. and Silvapulle, P. 2003), by comparing the characteristics of highly efficient farms with inefficient farms (Kelly, E. et al. 2012), or by changing the number of DMUs.

Gong, B.-H. and Sickles, R. C. (1992) compared the efficiency measures under DEA and SFA by using a Monte Carlo technique. Their model consisted of three inputs and one output. They used constant returns to scale to make a comparison between SFA and DEA more concise by removing the effect of scale economies and diseconomies. They found that SFA generally outperformed DEA when the functional form was close to the underlying technology. However, when the functional form was misspecified, then the DEA produced better results. Furthermore, the DEA outperformed SFA when the variables were highly correlated with inefficiency.

Galagedera, D. U. A. and Silvapulle, P. (2003) evaluated the sensitivity of the DEA's efficiency scores by omitting and including several important variables. They found that the DEA overestimates efficiency when including irrelevant inputs in the case of constant and decreasing return to scale and underestimates efficiency when omitting relevant variables. Furthermore, the effect of omitting an important variable was greater than the effect of including the irrelevant variable. So, they concluded that when omitting relevant variables, variable returns to scale should be used.

To check for the robustness of the DEA results, the farms with cost efficiency higher than 80% were removed and the cost efficiency of the years was re-estimated. This method of testing robustness is a modified version of resampling where the most efficient DMU's are removed and a new frontier is created. Simar, L. et al. (1998) have developed a bootstrapping method for DEA scores based on resampling to check the robustness of DEA.

The number of efficient farms and the average cost efficiency score is presented in Table 8.8.

Table 8. 8: The number of cost efficient farms and the average cost efficiency from 2006-2014 in the reduced sample

	No. of efficient farms	Average efficiency score	Total number of obs.
2006	7	0.72	817
2008	4	0.69	835
2010	6	0.79	747
2012	12	0.76	861
2014	10	0.82	633

In the year 2006, in the full sample, we had 885 farms whose average cost efficiency was 0.61. After removing the highly efficient farms[40], we are left with 817 farms. The cost efficiency of the reduced sample was estimated and the new average cost efficiency for the year 2006 was 0.72, so these farms could potentially reduce their costs by 28%.

In the year 2008, the full sample contained 92 farms with the average cost efficiency of 0.59. The reduced sample has 835 farms with the average cost efficiency equal to 0.69 implying that the farms could potentially reduce their costs by 31% while producing the same level of output. The number of efficient farms decreased from 9 farms in the full sample to 4 farms in the reduced sample.

[40] Highly efficient farms are those who have a cost efficiency score greater than 0.8. These farms can potentially reduce their costs by 20% while producing the same level of output.

In the year 2010, with the full sample, we had 939 farms which were then reduced to 747 farms after removing the highly efficient farms. The average cost efficiency increased from 0.69 in the full sample to 0.76 in the reduced sample.

Similarly, in the year 2012, the full sample contained 900 farms which were then reduced to 861 farms. The number of efficient farms in the full sample were 8 farms which increased to 12 farms in the reduced sample. Furthermore, the efficiency increased to 0.76 in the reduced sample from 0.61 in the full sample.

Lastly, in the year 2014, the number of farms decreased from 860 in the full sample to 633 in the reduced sample. The number of efficient farms also increased from 7 in the full sample to 10 in the reduced sample. The average cost efficiency also increased from 0.72 in the full sample to 0.82 in the reduced sample.

By resampling, we see that the number of cost efficient farms remains low implying that fewer farms are allocative efficient however the overall efficiency has improved. The farms that were previously creating the frontier are removed from the sample moving the other DMUs closer to the new frontier. So, after removing the highly efficient farms from the sample, we found that the efficiency increased in the reduced sample. There was approximately a 10% increase in the efficiency (or decrease in inefficiency) over the years. The DEA defines the efficiency of a DMU by its relative position to the frontier created by the best performing DMUs. So, a change in average efficiency was expected as the removal of highly efficient farms shifted the frontier downwards. The distance between a DMU and the frontier decreased hence increasing the efficiency of the farms.

To accurately examine the robustness of the cost efficiency of the dairy farms, we can compare the difference in cost efficient and inefficient farms in the reduced sample with the full sample. The differences in the characteristics of cost efficient and inefficient farms are presented in Appendix 8.2.

Like in the full sample, the milk production per farm and the total income generated per farm was higher in the cost efficient farms compared to the inefficient farms and the differences were statistically significant. A higher milk production per farm was due to the higher milk yield per cow. So, the dairy cows in the cost efficient farms produced statistically more milk than the dairy cows in the cost inefficient farms in both full and reduced sample. Stocking intensity was also higher in the cost efficient farms. The cost efficient farms also generated higher income per cow and had input output ratio greater 1. So, the cost efficient farms could cover their costs of production through the income generated on the farm. Lastly, in both the full and the reduced sample, the cost efficient farms produced less GHG emissions per hectolitre of milk produced.

Lastly, we can look at the percentage reduction in inputs required by the cost inefficient farms to become effective and produce milk at minimum cost. The percentage reduction in inputs that could be achieved by the inefficient farms to produce the same level of output is presented in Table 8.9.

Table 8. 9: Percentage reduction in input quantities in the reduced sample (2006-2014)

	Labour Hours	Feed	Cows
2006	-30%	-40%	-8%
2008	-12%	-20%	-22%
2010	-15%	-24%	-11%
2012	-29%	-18%	-16%
2014	-24%	-11%	-5%

The reduction in inputs is according to the frontier created by the efficient farms. So, by removing the highly efficient farms from the sample, we can see that the percentage reduction in inputs that could possibly be achieved by inefficient farms has reduced.

In the year 2006, the farms in the full sample could reduce labour hours by 16%, feed quantity by 49% and the number of cows by 42%. The cost efficient farms determined these optimal reductions in inputs. When we removed the highly efficient farms from the full sample, we found that the inefficient farms could decrease the use of labour hours by 30%, feed quantity by 40% and the number of cows by 8%. The difference in the reduction in inputs in full and reduced sample shows that the results of DEA would change with the changing number of DMUs. In the full sample, we found that for the farms to increase their efficiency they need to reduce the quantity of feed purchased the most which were followed by the number of cows on the farm. However, in the reduced sample we find that although the largest source of inefficiency remains the large quantity of feed purchased by the farm the second largest source of inefficiency becomes the higher input of labour hours.

In 2008, the largest source of cost inefficiency was the large quantities of feed purchased by the farms (55%) in the full sample which was followed by labour hours (30%). However, in the reduced sample, the largest source of inefficiency was the higher number of cows which can be reduced by 22% followed by the large quantity of feed which could be reduced by 20%. The labour hours can be reduced by 12%.

Similarly, in other years (2010, 2010, and 2014) the percentage reduction in inputs in the full and reduced sample differed, but it was to be expected as a new frontier was created. However, the largest source of inefficiency in the reduced sample remained the high quantity of feed purchased by the farms like in the full sample. If the inefficient farms reduce their input usage according to the percentages given in Table 8.7 and 8.9, the inefficient farms can become efficient.

8.4.3. Convergence

After estimating cost efficiency in the previous section, we classified farms into efficiency score brackets. By looking at Figure 8.1, we saw that there was an increase in the number of farms in higher efficiency score brackets. It indicated that the cost efficiency over the years is increasing. However, we cannot make it a conclusion as DEA is a relative efficiency measure and there are a different number of DMUS over the years which makes year to year comparison difficult. So, we cannot conclude just by looking at the data that there is some efficiency convergence. So β and σ-convergence of cost efficiency was estimated to determine if there is any convergence in the efficiency. The β- convergence was used to test for the hypothesis that the regions with lower cost efficiency would have faster growth rates than the regions with higher cost efficiency. The σ- convergence was used to determine whether the cost efficiency dispersion decreases over time.

This section of the chapter evaluates β and σ-convergence in cost efficiency. This section of the chapter is divided into two sub-sections. In the first section, regional convergence in cost efficiency is evaluated for nine regions in the two countries in the UK from 2006-2014. The two countries in the UK are Wales and England, where England has eight regions. The second section estimates convergence of farms that have reported their financial performance in the FBS from 2006-2014.

Regional convergence

The cost efficiency of farms in Wales and England was estimated in the previous section from 2006-2014. It was an unbalanced panel where the number of observations varied over the years.

To make it a balanced panel for efficiency convergence, the farms were grouped according to the regions in which they were located. The regional division was done according to NUTS 1 which classified nine regions for England and one region of Wales. Out of the nine regions in England, the region of London is excluded as it did not have any dairy farms. The remaining eight regions in England are North East, North West, Yorkshire, East Midlands, West Midland, East of England, South East and South West.

The average cost efficiency of these regions was calculated by taking the mean of the efficiency of the farms in these said regions. The number of farms in each region, the average cost efficiency of the regions and their standard deviation is presented in Appendix 8.3.

We test for the hypotheses that the regions with relatively low cost efficiency would catch up with the region with relatively high initial cost efficiency. In the basic form, β- convergence assumes that the regions with lower efficiency have faster growth rates than the regions with higher efficiency. Two models are estimated with the first model analysing absolute β-convergence between the countries. Since we are interested in whether there are differences in convergence in the efficiency of Wales and England, we use conditional convergence models where both the countries can have different steady state efficiency levels and different convergence rates. So, the second model analyses β-convergence within the countries.

Model 1: Absolute β-Convergence

The absolute β-convergence of cost efficiency is estimated for 9 regions in the UK. Following Fung, M. K. (2006) and Daley, J. et al. (2013), the absolute β-convergence is estimated using the equation:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + u_{i,t} \tag{8.7}$$

Where:

$CES_{i,t}$: Cost efficiency score of farm *i* at time *t*

$TREND_t$: Time trend

$u_{i,t}$: Stochastic disturbance

A negative value of β is a necessary condition for convergence. If the value of $\beta>0$, then there is divergence. The larger the absolute value of β, the faster the speed of convergence is. The coefficient of *TREND* term identifies the steady state efficiency improvement path for the whole industry (Daley, J. et al. 2013). Table 8.10 presents the results of Model 1.

The results of convergence of efficiency for years 2006 to 2014 is presented in the first row of Table 8.10. The subsequent rows present the results of separate sub-periods. The coefficient of the lagged term of cost efficiency is negative and significant which shows that there is efficiency convergence with and between the countries from 2006-2014. The estimates of β coefficient indicate that there is absolute β –convergence.

The regions which have lower initial average cost efficiency would converge at a faster speed than the regions having higher cost efficiency. This is because the further a region is from the frontier, the faster the speed of convergence would be (Daley, J. et al. 2013).

Table 8. 10: Absolute β-convergence (2006-2014)

		β	λ	α	Adj. R^2
2006-2014	Coefficient Std. error	-1.643 *** (0.163)	0.028 *** (0.006)	0.956 *** (0.100)	0.752
2006-2008	Coefficient Std. error	-0.625 (1.337)		0.379 (0.813)	-0.108
2008-2010	Coefficient Std. error	-1.282 *** (0.155)		0.851 *** (0.094)	0.894
2010-2012	Coefficient Std. error	-0.327 * (0.166)		0.147 (0.114)	0.266
2012-2014	Coefficient Std. error	-0.138 (0.419)		0.186 (0.255)	-0.125

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

The estimates of β were not significant for the years 2006-2008 and 2012-2014 which indicated that there was no convergence. In the years 2008-2010, there was a strong evidence β-convergence. Although there was some evidence of β-convergence in 2010-2012, the evidence was weak implied by the significance at 10%. The convergence in cost efficiency for the whole sample (2006-2014) is driven mainly by the period 2008-2010.

The coefficient of the trend term is positive and significant implying that efficiency is improving in the industry. The regions with low efficiency grew at a faster rate than the regions with relatively high efficiency. The region of East Midlands, East of England and the South West had low levels of cost efficiency in the initial period and their efficiency grew much faster than the rest and grew at a rate above an average of the whole industry. So, the regions that were furthest from the frontier converged faster than the regions that were closer to the frontier.

Model 2: Conditional *β*-Convergence with regional dummy

The β-convergence of cost efficiency among regions is also estimated. A regional dummy is included to allow for the variable speed of adjustment speed between the farm in Wales and England. The regional dummy with time trend would allow evaluating possible differences in the trend path of efficiency improvement. So, Model 1 is modified to be:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + \gamma TREND_t * DCOUNTRY + \vartheta CES_{i,t-1} * DCOUNTRY + u_{i,t} \quad (8.8)$$

Where:

$CES_{i,t}$: Cost efficiency score of farm *i* at time *t*

$TREND_t$: Time trend

$DCOUNTRY$: Country dummy that takes the value of 1 if Wales and 0 if England

$u_{i,t}$: Stochastic disturbance

If the value of $\beta < 0$ then there is efficiency convergence. If $\gamma \neq 0$, then the farms in Wales and England have different steady states. If $\vartheta \neq 0$, then the farms in Wales and England have different convergence rates. The results of Model 2 are presented in Table 8.11.

Table 8. 11: Conditional *β*-convergence (2006-2014)

	Coefficient		Std. error
β	-1.600	***	0.141
λ	0.022	***	0.006
γ	0.065	***	0.018
ϑ	-0.377	***	0.104
γ	0.952	***	0.086
Adj. R^2	0.817		

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

The estimates of β are negative and significant implying efficiency convergence. The regions with higher cost efficiency would converge slower than the regions with lower cost efficiency. The estimates of β are similar in both Model 1 and Model 2 which suggests that the speed at which the average cost efficiency converges across regions is not substantially different from the speed at which average efficiency converges for the farms within each country.

The country dummy captures the effects that are common to all the regions within the country. The interactive term of the country and lagged cost efficiency is negative and significant which suggests that the farms in Wales converge faster than the farms in England.

The interactive term of country and time trend is positive and significant which suggests that Wales and England have different steady states. The trend efficiency path of average cost efficiency of Welsh farms is higher than that of the industry.

The steady state values of efficiency improvement for farms in Wales (CES_W^*) and England (CES_E^*) is given as:

$$CES_W^* = \frac{\alpha + (\lambda + \gamma)TREND}{\beta + \vartheta} = 0.044$$

$$CES_E^* = \frac{\alpha + \gamma TREND}{\beta} = 0.041$$

The Welsh farms have a faster speed of convergence and the steady state path shows a faster improvement in efficiency over time than the English farms.

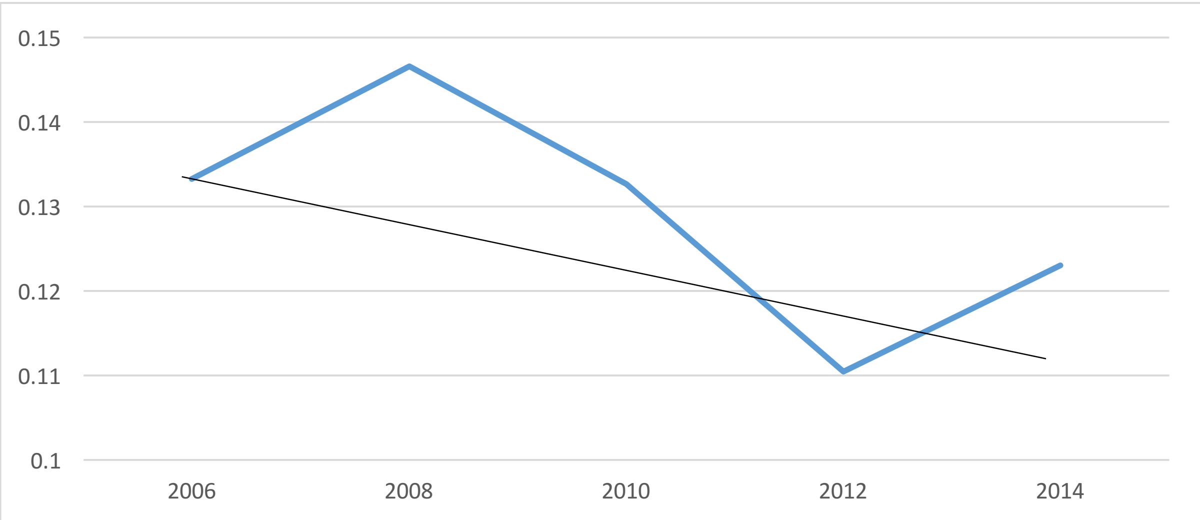
The β-convergence does have its limitations. The condition necessary for convergence (β<0) means that the regions with lower initial levels of efficiency would grow faster than those which high initial efficiency. This could then lead the regions with low efficiency to overtake the regions with high efficiency hence violating the idea of convergence. The limitations of β-convergence are addressed by σ-convergence. The σ-convergence assesses efficiency dispersion over time around the sector's average.

σ-Convergence

The *σ*-convergence addresses the limitations of *β*-convergence. The *σ*-convergence allows us to investigate how quickly each region's efficiency levels are converging to the average efficiency levels across regions for a given year. The *σ*-convergence can be visually analysed by looking at the standard deviation of efficiency over the years. If the deviation over the years is decreasing then, we can assume that there is *σ*-convergence.

The standard deviation and the trend of cost efficiency from 2006-2010 are plotted in Figure 8.2.

Figure 8. 2 : Standard Deviation of regional cost efficiency



The blue line plots the standard deviation and the black line roughly plots the trend. The deviation in cost efficiency increased from 0.133 in 2006 to 0.146 in 2008 but then declined to 0.11 in 2012. The deviation rose to 0.123 in 2014. The increase in deviation between the periods 2006 to 2008 is also reflected by the lack of *β*-convergence as shown in Table 8.10. The regions converged in the year 2008 to 2012 which is shown by the decline in the standard deviation. The regions would converge when the dispersion in the cost efficiency decreases over time. Then finally in the years 2012 to 2014, there was no convergence as shown by the increase in the standard deviation in 2014. Overall, the trend of standard deviation is declining which shows that there is efficiency convergence over time. We can also use specification by Parikh, A. and Shibata, M. (2004) to measure σ- convergence for panel data (equation 8.6) The results are presented in Table 8.12.

Table 8. 12: σ-convergence of regions

	Coefficient
ρ Std. error	0.000 (0.005)
ϕ Std. error	-0.966 *** (0.184)

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

The intercept terms are not statistically significant implying intercept being equal to zero. The term ϕ implies convergence over time. A negative value of ϕ shows that each region's cost efficiency is converging to the average level of the group and so efficiency dispersion is decreasing over time.

Convergence of individual farms

In the previous section, we looked at the β-convergence cost efficiency in UK regions. To get an accurate representation of β-convergence, we take a balanced panel. These are the farms that have reported their farming activities in the FBS from 2006-2014. So, the sample of farms has reduced to 320 farms from 2006-2014. Their average cost efficiency scores are presented in Appendix 8.4. A total of 7 model were evaluated for β-convergence with different structural variables to determine convergence in cost efficiency. The models are presented below.

Model 1:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + u_{i,t} \tag{8.9}$$

Model 2:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + \gamma TREND_t * DCOUNTRY + \vartheta CES_{i,t-1} * DCOUNTRY + u_{i,t} \tag{8.10}$$

Model 3:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + \vartheta CES_{i,t-1} * DCOUNTRY + \delta CES_{i,t-1} * DUAA + \zeta CES_{i,t-1} * DCOWS + u_{i,t} \tag{8.11}$$

Model 4:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + \vartheta CES_{i,t-1} * DCOUNTRY + \delta CES_{i,t-1} * DUAA + \zeta CES_{i,t-1} * DCOWS + \eta CES_{i,t-1} * DFEED + u_{i,t} \quad (8.12)$$

Model 5:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + \vartheta CES_{i,t-1} * DCOUNTRY + \eta CES_{i,t-1} * DFEED + \kappa CES_{i,t-1} * DINTENSITY + u_{i,t} \quad (8.13)$$

Model 6:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + \vartheta CES_{i,t-1} * DCOUNTRY + \kappa CES_{i,t-1} * DINTENSITY + u_{i,t} \quad (8.14)$$

Model 7:

$$\Delta CES_{i,t} = \alpha + \beta CES_{i,t-1} + \lambda TREND_t + \kappa CES_{i,t-1} * DREGION_j + u_{i,t} \quad (8.15)$$

Where:

$CES_{i,t}$: Cost efficiency score of farm *i* at time *t*

$TREND_t$: Time trend

$DCOUNTRY$: Country dummy that takes the value of 1 if Wales and 0 if England

$DUAA$: Dummy for area that takes the value of 1 if the farms size ≥ 130 hectares an 0 if the farms size <130

$DCOWS$: Dummy for the herd size that takes the value of 1 if the number of cows ≥ 130 hectares an 0 if the number of cows < 130

$DFEED$: Dummy for the cost of feed per cow that takes the value of 1 if feed cost per cow ≥ £500 hectares and 0 if feed cost per cow < £500

$DINTENSITY$: Dummy for the intensity of the farm that takes the value of 1 if the number of cows ≥ 130 hectares and farms size <130 and 0 if the number of cows < 130 and farms size ≥ 130 hectares.

$DREGION_j$: Dummy for the regions *(j=1,2,…,9)*

$u_{i,t}$: Stochastic disturbance

The Model 1 (equation 8.9) is the baseline model in which the growth of cost efficiency is regressed on the lagged value of cost efficiency and a time trend. We find that there is β-convergence in cost efficiency. The farms with lower cost efficiency scores converge faster than the farms with higher cost efficiency. The time trend is positive and significant implying that the efficiency is improving over time.

In the Model 2 (equation 8.10) , we included a dummy for the country of Wales and England. England was taken as the base country. We find evidence of β-convergence like in Model 1. The coefficient of the interactive terms of the country dummy and lagged cost efficiency is negative and significant implying that the farms in Wales converge at a faster speed than the farms in England. The coefficient of trend term remains the same as in Model 1, implying an improvement in efficiency over time.

In Model 3 (equation 8.11), we included two structural variables to Model 2. The variables of the area and the herd size, representing the number of cows, were added as a dummy to see if large farms converged at a faster speed than the smaller farms. The area dummy took a value of 1 if the farm's area was greater or equal to 130 hectares. The dummy for herd size took a value of 1 if the farm had a herd size of more than 130 cows and took a value of 0 if the herd size of the farms was less than 130 cows.

We found evidence of β-convergence and improvement in efficiency path over the years. The regional dummies showed similar results to Model 2 where the farms in Wales converged at a faster speed. The coefficient of the interactive term of lagged cost efficiency and farm area was negative and significant implying that larger farms (area>= 130hectares) converged faster than the smaller farms (area<130hectares). The coefficient of the interactive term of lagged cost efficiency and the dummy representing the herd size on the farm is positive and significant implying that the farms with larger herd size would converge at a slower speed than the farms with smaller herd size.

In Model 4 (equation 8.12), another structural variable of feed cost per cow was added to the independent variables in Model 3. The variable of feed cost per cow was taken as a dummy variable which took the value of 1 if the feed cost per cow on a farm was greater than £500.

There was a strong presence of β-convergence like in the models before. The coefficient of the interactive term of lagged cost efficiency and feed cost per farm was negative and significant implying that the speed of convergence of farms that spent more than £500 on feed per cow had a faster speed of convergence of the farms that spend less than £500 on feed per cow. This is intuitive as increasing the cost of feed per farm or per cow would lead to farms being more inefficient.

Then we added another variable to the Model 4 to make it Model 5 (equation 8.13). However now we excluded the area and the herd size and added the variable of intensity. This variable reflected intensive practices on the farm. The intensity dummy was equal to 1 if the farm's area was less than 130 hectares but had more than 130 cows. So, the variable intensity represented the stocking intensity of a farm. The farms with smaller area and larger herd size would have higher stocking intensity than the farms with the larger area and smaller herd size.

There was evidence of β-convergence. As before, the farms that had a higher cost of feed per cow had a faster speed of convergence. The intensive farms, those with a smaller area and a larger herd size, had a slower speed of convergence than the farms that had a lower level of intensity.

In Model 6 (equation 8.14), we remove all the structural variables but only keep the regional dummy and the dummy that indicates the intensity of the farms. By removing other structural variables, the speed of β-convergence increases. The speed of convergence of Welsh farms remained faster than the speed of convergence of English farms. The intensive farms have a slower speed of convergence in the cost efficiency than the less intensive farms.

In the last model, Model 7 (equation 8.13), we removed all the structural variables and included regional dummies. These regional dummies were created according to NUTS 1. So, we have nine regions; North East, North West, Yorkshire, East Midlands, West Midland, East of England, South East, South West and Wales. Wales was taken as the base region. We found strong evidence of β-convergence. Including regional dummies in the model increased the speed of convergence. The coefficient of the interactive term with lagged cost efficiency and regional dummies was significant for Yorkshire and West Midlands at 5% significance level and South West at 10% significance level. So, with England, the speed of convergence varied from region to region. Yorkshire, West Midlands and South West had a slower speed of convergence of cost efficiency than the rest of the regions in England and Wales.

In all the models, we find strong evidence of β-convergence. The farms with lower cost efficiency in the initial period have a faster speed of convergence than the farms with initially higher cost efficiency. The farms with lower cost efficiency are eventually catching-up. The speed of convergence of Welsh farms was found to be faster than the speed of convergence in English farms. In England, regions like Yorkshire, West Midlands and the South West had a slower speed of convergence than the rest of the regions.

Furthermore, larger farms in terms of area converged faster whereas larger farms in terms of the herd size converged at a slower speed the intensive farms, those who had smaller area farms and had a larger herd size converged at a slower speed than the farms that were less intensive. Lastly, the farms that spend more on the cost of feed per cow converged at a faster speed than the farms than spent less than £500 on feed per cow. In all the models, we found improvement in efficiency over time.

The results that there is a strong presence of β-convergence within and across the regions and countries in the UK for cost efficiency. It indicates that the farms are learning and that there is an improvement in efficiency over time suggesting that the catch-up effect is due to farms effectively utilising their inputs to reduce their costs.

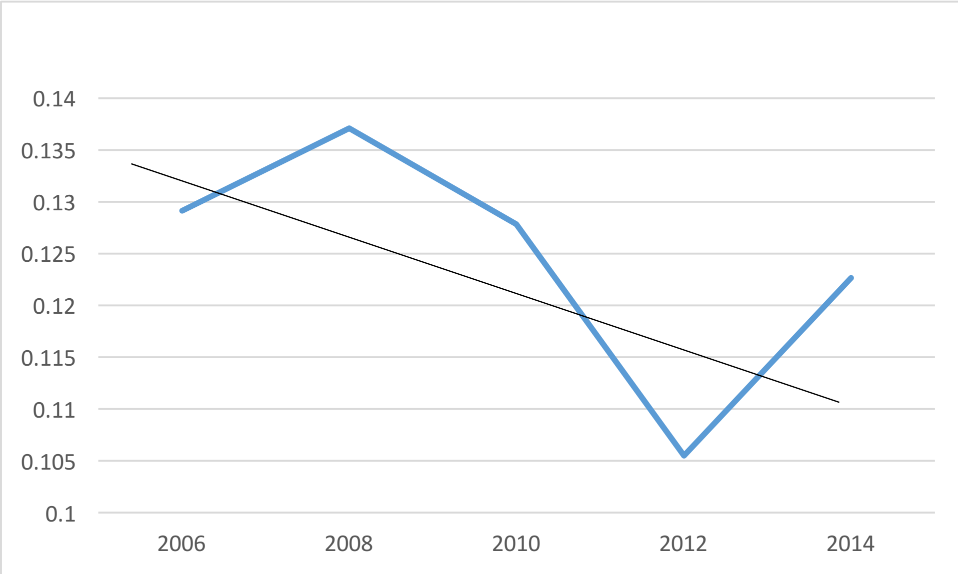
Table 8. 13: Absolute and conditional β-convergence for balanced panel

	1	2	3	4	5	6	7
β **Std. Error**	-0.530 *** (0.025)	-0.523 *** (0.025)	-0.553 *** (0.026)	-0.526 *** (0.028)	-0.509 *** (0.027)	-0.538 *** (0.025)	-0.556 *** (0.026)
TREND **Std. Error**	0.029 *** (0.003)	0.029 *** (0.003)	0.030 *** (0.003)	0.032 *** (0.003)	0.032 *** (0.003)	0.030 *** (0.003)	0.029 *** (0.003)
DCOUNTRY **Std. Error**		-0.030 *** (0.011)	-0.037 *** (0.011)	-0.038 *** (0.011)	-0.034 *** (0.011)	-0.033 *** (0.011)	
DAREA **Std. Error**			-0.063 *** (0.011)	-0.061 *** (0.011)			
DCOWS **Std. Error**			0.042 *** (0.011)	0.045 *** (0.011)			
DFEED **Std. Error**				-0.032 *** (0.0120)	-0.033 *** (0.012)		
DINTENSITY **Std. Error**					0.036 0*** (0.013)	0.034 *** (0.013)	
DREGION1 **Std. Error**							0.039 (0.024)
DREGION2 **Std. Error**							0.013 (0.017)
DREGION3 **Std. Error**							0.051 ** (0.023)
DREGION4 **Std. Error**							0.018 (0.020)
DREGION5 **Std. Error**							0.045 ** (0.019)
DREGION6 **Std. Error**							0.043 (0.026)
DREGION7 **Std. Error**							0.030 (0.027)
DREGION8 **Std. Error**							0.024 * (0.015)
Intercept **Std. Error**	0.258 *** (0.018)	0.259 *** (0.018)	0.280 *** (0.018)	0.269 *** (0.019)	0.252 *** (0.018)	0.265 *** (0.018)	0.261 (0.018)
Adj. R^2	0.292	0.292	0.312	0.315	0.302	0.299	0.294

***σ*-convergence**

To show an improvement in cost efficiency over time, we plot the standard deviation of cost efficiency scores across the years in Figure 8.3.

Figure 8. 3: Standard deviation of individual farms



As before, the blue line plots the standard deviation of cost efficiency scores and the black line shows the trend. The slope of the trend has not been drawn according to the scale and only represents the downwards trend. We see a downward trend in the deviation for most the year which implies that the efficiency is improving over time for the farms in the sample. To accurately evaluate σ-convergence we estimated equation 8.6. The results are presented in Table 8.14.

Table 8. 14: *σ*-convergence for balanced panel

	Coefficient
ρ Std. error	-0.044 *** (0.006)
ϕ Std. error	-0.415 *** (0.048)

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

The coefficient ϕ is negative implying an improvement in efficiency over time for individual farms. The regional cost efficiency is improving faster over time than the cost efficiency improvement in the individual farms, shown by the absolute value of ϕ.

8.5. Improving farms' profitability

The current trend in the dairy sector in the UK shows declining producer numbers and increasing herd size and milk yield. Profitable farms have increased their business while the less profitable farms have exited the market. With the declining number of dairy producers in the UK, it has become increasingly important to increase farm's profitability so that farmers stay in business.

A farms' profitability can be increased by reducing production costs, by increasing the income or both. Costs can only be reduced by reducing the input quantities as the farms are too small to affect prices thus the farmers act as price takers. Farms can also increase their income by increasing output production.

The factors relevant in determining farm's profitability are discussed below.

Feed

The quantity of feed purchased per farm was similar for the cost efficient and the inefficient farms. The quantity of feed purchased per cow as higher for the inefficient farms at 10% significance level. The optimal quality of inputs suggested that the inefficient farms could potentially reduce the quantity of feed purchased per farm by 16-55% from 2006 to 2014. The large quantities of feed purchased by farms were the largest source of their inefficiency especially with regards to the costs.

The quantity of feed estimated may not give an accurate representation of the quantity of feed used on the farms.

Firstly, we may have problems with the estimation of the quantity of the feed. The quantity of feed is calculated by dividing the total cost of feed with the unit price taken from ADHB. The unit price is an average price of the feed. The price of feed varies from month to month and varies from type to type. So taking a single unit price without knowing the type of feed used on the farm would not accurately represent the whole picture.

So it is essential to know the type of feed and its composition used on the farms. Secondly, the quantity of feed purchased by a farm also depends on the storage space that the farm has. If a farm has more storage space, then they would purchase higher quantities of feed especially if it is available at a lower cost. The farms will also purchase large quantities of feed if they believe that the price might rise in the future due to lack of supply in the coming month due to adverse weather like extreme flooding or drought. So, these factors also need to be examined before directly reducing the feed purchased by the farms.

However, other studies have also found that the feed costs have negatively affected the farm's profitability. Kauffman, J. B. and Loren, W. T. (1986) found a negative impact of feed purchased on the income of farms and emphasized on the importance of controlling the quantity of feed purchased by farms. Schoor, A. and Lips, M. (2018) also found that feed per cow contributed negatively towards a farms' economic performance.

Factors such as breeding, animal fertility and management practices have a long-term impact on a farm's productivity, however, the financial effects of changes in feed can be easily observed in the short term. Animal feed is the most significant cost associated with dairy farming (VandeHaar, M. J. et al. 2016) and improvement in animal feed can vastly improve farms' profitability. However, animal feed not only has a positive effect on the production of milk, but it also has either a negative or positive effect on the labour requirement, machinery and overall variable costs. The quantity and the quality of feed given to an animal also determine the amount of GHG emissions.

Specific steps can be taken for cost effective milk production. Firstly, the farmers should identify the requirements of feed needed for the farm. This entails knowing the number and the type of cows to be fed, their calving pattern, the quantity of feed likely to be required, area on which forge grows and the yield and quality of the forage.

The farms should also ensure that the feed is correctly stored, as wastage can lead to unnecessary and avoidable costs. So, such feeding systems should be in place that minimises wastage. Feeding systems depend on a variety of factors that include the production objectives, labour availability, cow genetics and accommodation.

<u>Milk Yield</u>

Milk yield is a strong indicator of a farm's profitability. A farm can increase its income by increasing the output it produces. The main output of dairy farms is milk production. Approximately 60% and more of the total income on a farm is generated through the sales of milk. Thus, an increase in milk production per farm can lead to an increase in the farm's profitability. Two ways can achieve an increase in milk production: either increasing the number of cows on the farm or increasing the milk production per cow. Increasing the number of cows on a farm is more natural as the farmer only requires capital to purchase more cows. We find that the cost efficient farms have higher stocking intensity than the inefficient farms and that the cost efficient farms also produce significantly more milk per cow. So, by increasing the number of cows on the farms and by keeping the land area as before, the inefficient farms would see a rise in stocking intensity which might contribute to an improvement in farms' efficiency. Literature suggests that there is a positive relationship between stocking intensity and farms' profitability (Schoor, A. and Lips, M. 2018) .

Schoor, A. and Lips, M. (2018) found that an additional tonne of milk produced by a cow could potentially increase annual income by one-tenth. Similarly Kauffman, J. B. and Loren, W. T. (1986) found that milk production was an essential factor in farms' probability of success. A farms' success refers to its ability to generate profit. They found that by increasing milk production per cow by 10%, the probability of a farm being successful rose 3%. Other studies (Ford, S. A. and Shonkwiler, J. S. 2016; Gloy, B. A. et al. 2016) also showed that an increase in milk produced per cow was positively related to a farm's profitability.

The milk production per cow was significantly higher in cost effective farms compared to cost inefficient farms. The cost efficient farms also had a higher stocking intensity. The cows in cost efficient farms produced 46% more milk than the cows in the cost inefficient farms.

An increase in milk produced per cow signalled some latent characteristics of farm's management. Higher milk yield indicated farmers' ability to apply production techniques and improved feeding practices (Gloy et al. 2016). Milk yield can be increased through genetics, feeding practices and lactation.

8.6. Conclusion

The cost efficiency of dairy farms in Wales and England was estimated using DEA. The data were taken from the FBS for the years 2006 to 2015. The inputs used in the efficiency measurement were labour hours (hours), feed (tonnes), the number of dairy cows on the farms and other variable costs (£) associated with farming. The outputs produced were the milk production (hectolitres) and the other income (£) generated on the farm through various activities. The data showed that the cost of inputs has risen over the course of 10 years. The wages per hour, however, have not increased as much as other input costs. The cost of feed per tonne and cost of cows per head increased 42-43% while other costs increased 24%. Wages increased 2% over the course of 10 years.

The income generated per hectolitre of milk rose 33% while other income fell 10% which indicated that farms are moving to more specialised production. The increase in income from a farm was not as high as the increase in the costs of a farm.

The costs per farm are rising more than the income per farm. Over the course of 10 years, the costs increased 58% while the income per farm rose 47%. The cost of producing one hectolitre of milk increased 24% over the course of 10 years while the total income generated per farm per hectolitre of milk sold only increase 14% over 10 years despite the price of milk increasing 34% over the years. The price/cost ratio suggested that for 4 years out of five, the dairy farms were unable to cover their cost of production with the income generated on the farms.

Due to increasing production costs and slow increase in income, it is becoming increasingly difficult for dairy farms to remain profitable. It is vital for them to use their inputs in a way which could minimise their cost of production or use their inputs in an efficient manner that maximise their revenue.

Results suggested that 99% of farms in the sample, were cost inefficient. The average cost efficiency score of the farms ranged from 0.59 to 0.72 from 2006 to 2014. So, the inefficient farm could potentially reduce their inputs costs by 28 to 41% and still produce the same level of outputs. The largest source of inefficiency was the purchase of feed.

We used DEA to obtain the cost efficiency scores for different years to consider changes in input prices that may affect efficiency. Then the convergence of cost efficiency among different regions in the UK was evaluated. We found evidence of β-convergence from 2006-2014. The evidence of convergence in the sub-period was also estimated, and we found that the results are not uniform across sub-periods. It was found that the regions with low efficiency like the East Midlands, East of England and the South West tend to grow faster than the regions with higher efficiency. A time trend was included to identify a steady state efficiency improvement path for the industry as a whole (Daley et al. 2013). The time trend was positive indicating an improvement in the efficiency path of the industry.

Then conditional β-convergence of cost efficiency was estimated by including a country dummy which interacted with the lagged cost efficiency and trend term. The conditional convergence showed within country β-convergence. The interaction of cost efficiency and county dummy helped to identify different speeds of adjustment for Wales and England. The speed of convergence in Welsh farms was faster than the speed of convergence in English farms. The estimates of β were similar in both absolute and conditional β-convergence which suggests that the speed at which the average efficiency converges across regions is not substantially different from the speed at which average efficiency converges for the farms with each country.

Then the convergence in cost efficiency for the farms that reported their final data in the FBS for all the years in the sample was estimated. It was found that their cost efficiency converged over the years. The farms in Wales converged at a faster speed than the farm in England. Furthermore, larger farms in terms of area converged faster whereas larger farms in terms of the herd size converged at a slower speed the intensive farms, those who had smaller area farms and had a larger herd size converged at a slower speed than the farms that were less intensive. Lastly, the farms that spend more on the cost of feed per cow converged at a faster speed than the farms than spent less than £500 on feed per cow. In all the models, we found improvement in efficiency over time.

The results that there is a strong presence of β-convergence within and across the regions and countries in the UK for cost efficiency. It indicates that the farms are learning and that there is an improvement in efficiency over time suggesting that the catch-up effect is due to farms effectively utilising their inputs to reduce their costs.

Some policies may be employed to increase the speed of convergence. In Chapter 7, we examined factors that may influence efficiency. We found that age negatively affected efficiency whereas the loans and intensity of dairy production improved efficiency. So, the government may make loans available for the farmers who want to intensify dairy production at low-interest rates. It might encourage farmers to take up more loans and invest in the farm hence improving efficiency. Furthermore, mentorship and training programs might help young individuals to join dairy farming.

8.7. Appendix

Appendix 8. 1: Revenue Efficiency

a) Methodology

The theory behind the estimation of revenue function and revenue efficiency is presented in Chapter 4. The constant returns to scale revenue efficiency model presented by Zhu, J. (2009a) is as follows:

$$\min \sum_{r=1}^{s} q_r^o \tilde{y}_{ro}$$

St:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \tilde{y}_{ro}$$

And

$$\lambda_j, \tilde{y}_{io} \geq 0$$

Where $i=1,2,....,m$, $r=1,2,....,s$ and q_r^o is the unit price of output r of DMU_0. The above model is for CRS. To convert this model to suit VRS, we need to add another equation:

$$\sum_{j=1}^{n} \lambda_j = 1$$

This condition allows the software to match DMUs against other DMUs of similar size. The revenue efficiency of DMU_0 (CRS or VRS) can be defines as:

$$\frac{\sum_{i=1}^{m} q_r^o y_{ro}}{\sum_{i=1}^{m} q_r^o \tilde{y}_{ro}^*}$$

b) Number of Revenue, Technical and Allocative efficient farms

Year	Revenue Efficiency	Technical Efficiency	Allocative Efficiency	Number of efficient farms
2006	0.64	1.57	1.00	33
2008	0.66	1.51	1.00	33
2010	0.75	1.33	1.00	44
2012	0.67	1.50	1.00	34
2014	0.76	1.32	1.00	35

c) Characteristics of revenue efficient and inefficient farms

	RE < 1		RE = 1			
	Mean	**SD**	**Mean**	**SD**	**P-value**	**Sig.**
UAA (ha/farm)	140	117	136	115	0.038	**
Cows (cows/farm)	132	82	204	193	0.029	**
Labour Hours (lh/farm)	7,319	3,783	7,722	6,408	0.002	***
Feed (t/farm)	396	326	499	573	0.112	
Other Costs (£/farm)	134,654	138,956	182,462	194,153	0.275	
Milk Produced (hl/farm)	9,134	6,259	15,475	13,811	0.000	***
Other Income (£/farm)	131,214	151,544	123,636	138,191	0.005	***
Total production cost (£/farm)	426,110	305,540	568,534	515,144	0.177	
Total income (£/farm)	395,867	284,011	567,782	494,723	0.006	***
Milk yield (hl/cow)	69	16	76	35	0.000	***
Stocking Intensity (cows/ha)	1	1	2	1	0.000	***
Labour hours per cow (lh/cow)	55	33	38	50	0.000	***
Feed per cow (t/cow)	3	1.4	2.45	1.93	0.000	***
Other costs per cow(£)	1,019	826	896	1,588	0.005	***
Other income per cow(£)	993	1,335	607	1,814	0.000	***
Production cost per cow(£/cow)	3,226	1,265	2,792	2,325	0.000	***
Total income per cow (£/cow)	2,996	1,397	2,788	2,087	0.285	
Output input ratio (£)	0.93	0.17	1	0.22	0.000	***

Note: *** denotes significance level <0.01 , ** denotes significance level <0.05 and * denotes significance level <0.1

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

Appendix 8. 2: The differences in cost efficient and inefficient farms for the reduced sample

	CE <1		CE = 1			
	Mean	SD	Mean	SD	P-value	Sig.
UAA (ha/farm)	142	119	181	146	0.349	
Cows (cows/farm)	127	76	238	199	0.028	**
Labour Hours (lh/farm)	7,274	3,673	10,166	7,897	0.447	
Feed (t/farm)	382	305	716	748	0.262	
Milk Produced (hl/farm)	8,519	5,545	17,579	14,119	0.005	***
Total production cost (£/farm)	281,812	171,042	494,532	432,758	0.113	
Total income (£/farm)	245,773	174,316	512,305	430,509	0.006	***
Milk yield (hl/cow)	65	16	70	15	0.029	**
Stocking Intensity (cows/ha)	1.14	0.61	1.33	0.57	0.027	**
Labour hours per cow (lh/cow)	66	35	53	24	0.002	***
Feed per cow (t/cow)	2.97	1.44	2.78	1.27	0.460	
Production cost per cow(£/cow)	2,260	622	2,100	486	0.221	
Total income per cow (£/cow)	1,851	535	2,054	510	0.016	**
Output input ratio (£)	0.85	0.23	1.01	0.25	0.000	***
GHGE per hectolitre of milk (CO_2 eq/hl)	81	45	72	24	0.018	**

Note: *** denotes significance level <0.01, ** denotes significance level <0.05 and * denotes significance level <0.1

Source: Own calculations based on data from DEFRA, N. A. f. W. (2008a,2008b,2010,2011,2014a,2014b); Duchy College, R. B. S. (2014,2015,2016,2017)

Appendix 8. 3: regional convergence

a) The number of farms in a region

	2006	2008	2010	2012	2014
North East	24	25	24	26	24
North West	124	124	137	139	131
Yorkshire	51	55	59	52	51
East Midlands	77	77	71	71	61
West Midlands	78	78	83	88	91
East of England	40	40	39	31	29
South East	55	57	52	41	35
South West	182	211	225	206	199
Wales	254	254	249	246	239

b) The average cost efficiency score of farms in a region

	2006	2008	2010	2012	2014
North East	0.602	0.636	0.703	0.618	0.700
North West	0.611	0.648	0.686	0.609	0.724
Yorkshire	0.637	0.638	0.690	0.629	0.745
East Midlands	0.599	0.603	0.677	0.600	0.698
West Midlands	0.603	0.604	0.681	0.608	0.674
East of England	0.599	0.605	0.659	0.590	0.718
South East	0.609	0.614	0.666	0.579	0.690
South West	0.597	0.613	0.670	0.606	0.698
England (all)	0.605	0.620	0.677	0.606	0.705
Wales	0.612	0.500	0.730	0.632	0.745

c) The standard deviation of cost efficiency scores in a region

	2006	2008	2010	2012	2014
North East	0.103	0.137	0.110	0.101	0.124
North West	0.131	0.159	0.126	0.097	0.114
Yorkshire	0.159	0.168	0.140	0.108	0.107
East Midlands	0.106	0.135	0.117	0.102	0.100
West Midlands	0.135	0.155	0.144	0.120	0.149
East of England	0.120	0.168	0.139	0.145	0.121
South East	0.161	0.169	0.133	0.118	0.128
South West	0.139	0.132	0.131	0.108	0.119
Wales	0.131	0.094	0.131	0.112	0.122

Appendix 8. 4: Average cost efficiency of individual farms

	Mean	St. Dev
2006	0.616	0.129
2008	0.578	0.137
2010	0.704	0.128
2012	0.614	0.106
2014	0.724	0.123

9. SUMMARY, DISCUSSION AND CONCLUSION

This study evaluated dairy farm efficiency while accounting for environmental effects associated with dairy farming systems. Sustainable intensification (SI) was the underlying context of this research. The environmental aspect of sustainability was taken into account by calculating greenhouse gas (GHG) emissions using the Intergovernmental Panel on Climate Change (IPCC) guidelines.

The efficiency of dairy farms was estimated using data envelopment analysis (DEA). DEA is a non–parametric method of estimating efficiency which creates a frontier over the data. Efficiency is measured as a distance between the farm and the frontier. The data used for this study taken from the Farm Business Survey (FBS) from 2006 to 2015. Since the research was focused on dairy farms, data were only taken from the farms with more than 20 cows to eliminate farms rearing cows for personal use. The number of farms over the years ranged from 418 farms to 477 farms. The sample size over the 10 years was relatively small so to increase the size of the sample we pooled two years of data into one-year which created five separate 'years'. The sample size increased and varied between 860 farms to 939 farms. The inputs used in estimating efficiency were the utilised agricultural area (UAA) in hectares, the labour hours worked on the farm, the number of dairy cows, the cost of feed and the other costs associated with dairy farming. The outputs of dairy production were milk production in hectolitres, other income generated on the farms and the GHG.

A variety of tests, including cluster analysis, Tobit Regression and convergence was estimated, and a few essential results came forward. Key findings, from 4505 dairy farms include:

- Average dairy herd is increasing. Over the ten year period, the herd size increased 32% in Wales and 38% in England.
- Dairy cows are becoming more productive as they are producing more milk in 2015 than in 2006. Over the ten year period, the milk produced by a dairy cow increased 13% in Wales and 6% in England.
- With an increase in herd size, other inputs like labour hours, the cost of feed and the other costs have increased on farms.
- Dairy farming in Wales and England is dominated by farmers aged 50+ years

- In Wales and England, emissions from dairy farms are decreasing overall. The GHG emissions per litre of milk decreased 6% in England and 9% in Wales from 2006 to 2015.
- Using the K-means cluster analysis, we were able to separate farms into two clusters, intensive and less intensive farms. We found that intensive farms produced almost three times as much milk per hectare as the less intensive farms since the intensive farms had double the stocking intensity of the less intensive farms. Intensive farms also produced 17% to 24% more milk per animal than the less intensive farms and generated 20% to 29% less GHG emissions per hectolitre of milk.
- Using undesirable DEA, we estimated the efficiency of dairy farms by taking into account 'good' and 'bad' output. The good output was milk production, and other income and the bad output was GHG emissions. The results suggested that the intensive farms had higher average efficiency than the less intensive farms.
- Wales had a higher proportion of efficient farms, but its average efficiency was lower than most other UK regions implying that large deviations were present among the farms.
- Using Tobit regression, we found that geography does influence a farm's efficiency.
- The cost of production of a hectolitre of milk ranged from £30.2 in 2006 to £36.53 in 2014.
- The price of a unit of milk barely covers the cost of milk when subsidies are not included in the price of milk.
- Overall cost efficiency is improving over the years.
- We find evidence of β and σ convergence in cost efficiency implying that the regions with lower cost efficiency are increasing their efficiency faster than the regions with initially higher cost efficiency. So, the regions with lower efficiency would eventually catch up to the regions with higher cost efficiency.

9.1. Research Questions

The research was set out to answer four questions. The research questions are examined below in detail.

Research Question 1: Does the intensification of dairy farms reduce GHG emissions

Research Question 2: Does intensification improve a farms' efficiency

The research question 1 and 2 were answered together in Chapter 6 where we assess dairy farm's efficiency and used cluster analysis to create separate groups of intensive and less intensive farms.

To answer research equation 1, the K-means cluster analysis was employed to separate the farms according to their intensity characteristics like milk production per cow and per hectare, cows per hectare (stocking intensity) and GHG emission per hectare. Two clusters were formed based on these characteristics: intensive farms and less intensive farms. We had made some prior assumptions about the characteristics of the intensive farms based on literature which suggested that the intensive farms have higher milk production per cow, they have higher milk production per hectare and the stocking intensity on the intensive farms is higher. No prior assumptions were made about the GHG emission on the intensive farms as the literature has shown mixed results.

We found that the farms that were classified in the intensive farm cluster produced anywhere from 26 to 34% less GHG emission per hectolitre of milk than the less intensive farms over the period of 10 years. By taking GHG emissions as a proxy indicator of environmental sustainability, we can safely say that the intensive farms are more environmentally sustainable

To answer the research question 2, we then assess the efficiency of dairy farms using undesirable DEA by Seiford, L. M. and Zhu, J. (2002). The undesirable DEA model allowed us to estimate efficiency by creating a frontier in which the good output like milk production and other income was maximised, and the bad output (GHG emission) was minimised. The average efficiency score over a10 year period, for farms in the sample, ranged from 1.042 to 1.080. So, an average farm in the sample could potentially increase their output production by 4.2 to 8.0 % while using the same level of inputs. The output targets suggested that if the inefficient farms mimicked the efficient farms' production systems then they could potentially increase their milk production by 4-8%, other income by 6-12% and reduce the GHG emission by 18-35% over the sample years. The average efficiency of intensive and less intensive farms was measured, and we found that the intensive farms were more efficient than the less intensive farms. The efficiency score of intensive farms ranged from 1.038 to 1.073, and the average efficiency of the less intensive farms ranged from 1.044 to 1.084. In four out of the five years, the average technical efficiency score was significantly lower in intensive farms compared to the less intensive farms. The higher efficiency score implied higher inefficiency amongst farms. Furthermore, a higher percentage of intensive farms were technically efficient compare to the less intensive farms. The optimal targets suggested that the less intensive farm could potentially increase their good output and reduce their bad output by a far greater percentage than the intensive farms.

So, we could conclude that the intensive farms were using their inputs in an optimal proportion than the less intensive farms. Dairy farms that performed better economically also exhibited a higher degree of environmental performance. The economic performance and environmental performance go hand in hand (Jan et al. 2012). So, by improving the economic performance of dairy farms, the farms tend to improve their environmental performance and vice versa.

Research Question 3: What factors determine a farm's efficiency? Does the location of the farms affect their efficiency? Are there non-controllable factors that may influence efficiency?

The research question 3 was answered in chapter 7 where we assessed the technical efficiency of dairy farming using a simple output-oriented DEA and then using Tobit Regression, analysed the factors that may influence a farms efficiency. The factors included are the age of the dairy farmer, education, the intensity of the farm, the gross value added (GVA) of the region in which a farm is located, the amount of loans, the cost of land, the tenure of the farm implying if the farm is tenanted or operated by the farmer and lastly the region in which a farm is located.

The factors like cost of land, the tenure of the farm and the intensity of the farm represented the importance of land in dairy farming. The cost of the land negatively influences the efficiency of the farm. The expensive the farm area is, the less likely is a farmer to purchase more land. If the land is cheaper, then the farmer would be willing to purchase more land for farm activity. Furthermore, arable land is more expensive than the land for pasture. So, the expensive land would be used by the farmer for activities that would generate higher profits like planting cereal crops.

The tenure term had a positive and significant relationship with efficiency. The farm's efficiency was positively affected if the owner operated the farm. The owner has more interest in the farming activities and would be willing to put in an extra effort. Furthermore, the ownership of the good quality land would be high as the farmer would be expecting higher output.

We found that the intensity of a farm positively affected efficiency. So, the farms that were intensive i.e. had higher stocking intensity and produced more milk per cow and per farm increased a farms efficiency. The intensity of the farm signals the intensity of land use through stocking intensity. So, the land that is used intensively would positively affect the efficiency as more activity is occurring per hectare of land.

The results suggested that the younger farmers improved farms efficiency. The younger farmers are less biased toward change so they would be more willing to adopt new technologies that would increase efficiency. Furthermore, the managerial capability of a farmer decreases with age which would negatively affect efficiency.

The interaction of GVA with efficiency was found to have a negative relationship. The farms located in regions with higher GVA would decrease their efficiency. GVA is an indication of economic activity. In the UK, agriculture contributes 4-5% to the total GVA which suggests that the UK's reliance on agriculture is low. It is a stylized fact that agriculture is concentrated in areas with low economic activity. These areas are far from the big cities and so have a relatively lower rate of employment. So, the regions with lower GVA would have higher agricultural activities which would contribute to improvement in efficiency.

The loans positively affect the efficiency of a farm. When the farmer can secure a loan, he would invest that money into the farms. Additionally, the farms that can secure the loans would be the ones who are already profitable as otherwise, the banks would not give out loans.

Regional dummies suggested that all the regions in England's positively affected a farm's efficiency relative to Wales. Farms located in East of England and South East positively influenced efficiency more than any other region in the UK. We found that education of a farmer did not influence a farms efficiency.

Research Question 4: Did the Welsh and English dairy farms exhibit convergence in terms of cost efficiency from 2006-2014

This research question is answered in Chapter 8. The cost efficiency of farms is measure using DEA. The cost efficiency is a measure of minimum costs observed in the sample to the actual production costs of a farm. The average cost efficiency of farms in the sample ranged from 0.59 to 0.72 from 2006-2014 implying a potential reduction in production costs by 28% to 41% over the same period. A significant proportion of cost inefficiency was due to the quantity of feed purchased which was followed by the labour hours.

The convergence in cost efficiency was determined by β and σ-convergence. β-convergence suggests that the farms or regions with lower cost efficiency would increase their efficiency faster than the farms or regions having a higher initial cost efficiency. The σ-convergence measures the dispersion in efficiency over time.

Following the concept of β and σ-convergence by Barro, R. J. and Sala-i-Martin, X. (1992)and the specifications by Parikh, A. and Shibata, M. (2004) we found strong evidence of β and σ-convergence in cost efficiency for the region in the UK and individual farms. The regions with initial lower cost efficiency improved their efficiency faster over time than the regions that had higher initial cost efficiency. The region of East Midlands, East of England and the South West had low levels of cost efficiency in the initial period, and their efficiency grew much faster than the rest and grew at a rate above the average of the whole industry.

Then we checked for β-convergence in Wales and England and found that Wales converged at a faster rate than England and would eventually catch-up. Furthermore, we added structural variables to test for conditional convergence, and it applies if the growth in efficiency is negatively related to the initial levels of efficiency after holding all or some variable such as area, number of cows, the cost of feed per cow, the intensity of the farms and regions.

9.2. Policy recommendation

Balancing the future demand for food and supplying that food sustainably to the growing population is a key challenge for policy makers. Increasing food production needs to be sustainable while using existing knowledge and technology. An increase in agricultural output can be achieved through promoting best practise rather than though new knowledge or technologies (Eisler, M. et al. 2014). A yield gap exists within and between countries due to poor infrastructure, like lack of roads and storage facilities or limited access to markets. Although sustainable intensification is an answer to growing food demand and protection of the environment, there are other smaller measure that can be undertaken to improve food production. Agricultural productivity can be improved and food waste can be reduced though improvement in basic infrastructure, especially in low to middle income countries.

Reduction in food waste and improving governance of food systems can also cater to rising demand for food. It has been estimated that anywhere between 30 to 50% of food grown worldwide is wasted before it reached the consumer (Lundqvist, J. et al. 2008). In the UK, approximately 25% of purchased food was wasted by the households (WRAP 2009). Similarly, in other high income countries like the USA and Australia, anywhere between 15 to 25% of food is wasted at homes (Griffin, M. et al. 2009; Morgan, E. 2014).

Food wastage, in countries where primary source of income for individuals is from agriculture, can potentially be reduce though rising food prices which would provide incentive to avoid food wastage. An increase in food prices would raise income levels of the farmers thereby improving the quality of life. Increase in food prices would also allow the farmers to invest more in technology and build appropriate storage facilities to reduce post-harvest food waste. Food wastage in high income countries, like the UK, has been linked to relatively low food prices. An increase in food prices in these countries can potentially lead to reduction in food waste.

High income countries are also more likely to demand for more food (due to more disposable income) which requires land, water and energy for their production. Increasing demand for food by these countries have led to an overall increase in demand finite resources which has led to increase in competing for these resources thus placing more burden on the environment (Garnett, T. et al. 2013).

The Food Ethics Council (2010) suggested influencing demand for food though advocating consumption of foods using fewer resources has been suggested along with regulatory framework that promotes balanced diets. So, apart from improving efficiency of food systems, reduction in food waste and increase in food supply, the demand for food also needs to be addressed.

- The results from Chapter 7 suggest that intensive farms may be more environmentally and technically efficient. These farms would generate a higher output with lower GHG emissions. Furthermore, a higher portion of intensive farms were technically efficient compared to the less intensive farms, e.g. the intensive farms were using fewer inputs to produce their output while producing fewer GHG emissions. In this research, the intensity of the farm is reported by the higher stocking intensity on the farm. The stocking intensity has been shown to be a significant factor contributing to the differences between the technical and cost efficient and the inefficient farms.

This suggests that the policy might encourage farmers to intensify dairy production. Such policies could facilitate the expansion of a dairy farm by encouraging an increase in the herd size on the farm. For example, financial support may be provided to farmers who want to increase the number of animals on the farm. In additions fines or reduction in subsidies can be implemented on farms with low stocking intensity thus producing higher GHG emissions per hectolitre of milk to encourage the farmers to increase the herd size on their farms.

In this study, we have shown that intensive farms in the sample perform better than the less intensive farms by producing more milk per animal and emitting less GHGs per hectolitre of milk produced. Policies encouraging farmers to intensify production through increasing stocking intensity has been recommended. However, a lot of criticism has arisen about intensification especially regarding the welfare of animals. Until 1950, the farms were traditional in nature where they relied on labour for tasks like feeding, milking and removing the manure. Most of the farms were family farms where animals were cared for with kindness (Fraser, D. 2008). With the advancement in technology and a drive to increase production, the traditional farming systems have been replaced by confinement systems where the animals are kept indoors and tasks previously untaken by labour have been replaced by automated machines. Automation has also helped farms to increase the number of animals without placing an additional burden on the labour.

With increasing research in this field, ethical concerns have arisen from growing scientific knowledge regarding the welfare of animals. Human views have shifted to viewing animals as pets and a member of a family rather than viewing animals solely as a source of food or as a means of transportation. Some believe that the intensification of farms has led to the replacement of family farms into large corporation who are more concerned with profit than animal care (Fraser, D. 2008).

Gieseke, D. et al. (2018) conducted a study on the relationship between herd size and animal welfare on dairy farms. The study was conducted on 80 conventional farms with herd size ranging from 45 to 1,629 dairy cows. Animal welfare was assessed through the Welfare Quality Protocol (WQP) on feeding practices, housing conditions, overall animal health and appropriate behaviours of animals. They found a significant effect of herd size on good feeding implying that farms with larger herd size scored better than the farms with smaller herd size. They found no significant relationship between herd size and housing conditions, overall animal health and appropriate behaviours of animals. Studies like Adams, A. E. et al. (2017), Chapinal, N. et al. (2013), de Vries, M. et al. (2014) and Barker, Z. E. et al. (2010) evaluated the effects on herd size on animal health through the prevalence of lameness in dairy cows. Inconsistent results are found with studies that consider the relationship of herd size and lameness.

Adams, A. E. et al. (2017) and Chapinal, N. et al. (2013) found a negative association of herd size with lameness. They argued that larger farms are likely to have more personnel to manage lameness and animal health. Barker, Z. E. et al. (2010) found no relationship between lameness of animal and herd size but they found that other factors like damaged concrete in yards, cattle grazing on pasture also grazed by sheep, cows pushing each other or turning sharply at parlour entrance was a risk factor associated with an increase in prevalence of lameness. Studies like de Vries, M. et al. (2014) found that increasing herd size would have a positive effect on lameness.

- The results suggest that land ownership influences the efficiency of the farms positively. Approximately, 82% to 85% of farms in the sample years were owner-occupied farms. The attitude towards farming is different for the owner and the tenant which influences economic performance. Thus, policies can be introduced to support land ownership rather than tenancy.

  Financial constraints of an individual willing to purchase land are going to be an important policy reform targeting an increase in land ownership. Finance can be made available for individuals willing to buy land for agricultural purposes.

  However, care should be taken with regards to policy making for land ownership. Land ownership motivated by tax reforms may reduce agricultural efficiency, and the availability of agricultural land as an individual might want to own land solely for tax reduction and asset protection. This individual would not be motivated agriculturally and would purchase agricultural land for the protection of wealth. These individuals would hoard the land that would have been beneficial to the farming industry.

- We have seen that the older generation dominates the agriculture sector in the UK and the proportion of farmers aged 50+ years is increasing (Chapter 5.4.1). Furthermore, the general perception is that the older farmers would be more likely to exit the industry. DairyCo (2013) also found that that the younger farmers (under 40 years of age) wanted to increase their financial return by adopting new technology through expansion of farming activities whereas a larger percentage of older farmers (age 60+ years) wanted to leave dairy. Furthermore, they found that dairy farm profitability in England decreased by £6.81 per hectare with each additional year of age. We also found that age negatively affects efficiency.

  So, increasing the participation of younger farmers in dairy activities might improve efficiency. The contribution of young individuals to agriculture can potentially be increased through training and mentorship. Young individuals, who are entering or are willing to join the agricultural sector can significantly benefit from training and mentorship programs. Older farmers, who are more experienced can help younger farmers understand the workings on a farm.

  Programs may be implemented which make it easier for young individuals to obtain loans as they generally encounter difficulty in getting loans. The banks are more willing to lend to already established farmers rather than the individuals who are just entering the sector and have not yet proved their ability in running a business (CEC 1996). Countries like France and Denmark have adopted policies of financial aid catering specifically to the young farmers by reduced interest rate loans and grants (Gibbard, R. 1997) .
- In this study, we found that the only 1% of the farms in our sample were cost efficient, implying that only a small number of farms were producing desired output at minimum cost. Remaining 99% of the farms, could potentially on an average reduce their production costs by 28% to 41%. We found that major contributor to cost inefficiency was the quantity of feed purchased by the farms. In 4 out of 5 years, the farms on an average could potentially reduce their quantity of feed purchased by more than 30%. A variety of factor influence a farmer's decision to purchase feed. Firstly, the quantity of feed purchased depends on the number of animals on the farm and the breed of the animal. Secondly, it depends on how much grazing area is available to the farmer and thirdly it depends on the prices of the feed.

The cost of feed is an important aspect of a farm's decision to purchasing feed. The feed prices are volatile in nature due to the production systems. The demand is relatively inelastic and the supply is variable as it depends on a variety of factors outside anyone's control. Volatility in feed prices is not only affected by the demand and supply of feed but is also affected by changes in cost of fuel. Changes in oil prices affect feed production though changes in the cost of energy required for production. Volatility of agricultural markets threatens low income countries more due to their reliance on agriculture as a source of income. In such countries, a rise in feed prices has often been a major cause of increased hunger.

However, addressing the volatility in feed prices alone would not make livestock farming sustainable. The production of animal feed is a challenge for policy makers as they need to determine whether the crops or grains produced should be allocated for animal feed or for human consumption. A large portion of world's grain production is being used to feed animals. It has been estimated that 70% of grain in developed countries is consumed by animals.

A variety of recommendations have been put forward to address the issue of volatility in feed prices. Some suggest that reliance of animals on grains should be reduced whereas some suggests that humans should alter their food preferences. It has been suggested that the reliance for animal feed for ruminant animals, like cows, should include more hay, silage and high fibre crop residue, which is unsuitable for human consumption. The animals can graze marginal areas like mountainsides to help preserve fields for growing human food (Eisler, M. et al. 2014).

Studies have recommended transitioning from animal-based protein sources to plant-based protein. Di Paola, A. et al. (2017) compared water and carbon footprints of animal-sourced protein with plant-source protein to determine which food source performs better in terms of requiring fewer resources and GHG emissions. They found that the production of animal-sourced protein was 2.4 to 33 times more expensive in terms of land and water demand and emitted 2.4 to 240 times more GHGs than the plant-sourced protein.

9.3. Strengths and weaknesses

There are some limitations to this research. The first limitation is linked to the data collection. As mentioned before, the data for this research has been taken from the FBS. The FBS provides data on a small sample of farms and covers less than 5% of the total number of farm holdings in Wales and England. So, the results obtained by using the data from the FBS may be different from the results obtained using the whole population. Another problem with the FBS is that it is redesigned every few years which makes year to year the comparison difficult.

The second limitation is with regards to the inputs used in this research. We have not considered the different types of soil; fertiliser composition and feed quality that may affect the output production. These factors have been known to affect the output production, but due to the lack of availability of data, these variables have been ignored.

Thirdly, the application of DEA for estimating efficiency also have some weaknesses. DEA is a deterministic approach of measuring efficiency, so it does not distinguish between technical efficiency and statistical noise. So, the efficiency estimates obtained by the DEA may be biased if stochastic elements characterise the production.

Although estimating efficiency using DEA has a few drawbacks, its strengths outweigh the weaknesses. DEA allows us to estimate efficiency using multiple inputs to produce various outputs. DEA does not require a functional form, so no prior assumptions are made about the production function.

Furthermore, this is a one of a kind study where the convergence in cost efficiency is evaluated in a specific agricultural sector. Majority of the studies estimate convergence in the GVA of the agricultural industry or the efficiency of the whole industry. None of the studies on convergence has focused on a specific sector, especially in agriculture. In this study, we concentrate specifically on the dairy sector in Wales and England and determine convergence in cost efficiency.

Lastly, the estimates the GHG emissions are calculated using IPCC guidelines, and we have used the UK's specific emission factor values to represent the emissions from the dairy farming accurately.

9.4. Future Research

- One of the limitations of DEA is that it does not allow for hypothesis testing. We had to use a non-parametric Mann-Whitney U test to test for significant differences in efficiency. Simar, L. et al. (1998) introduced a method of bootstrapping in DEA which would allow hypothesis testing. Bootstrapping is a process which involves mimicking the data of the underlying model to produce multiple estimates. Bootstrapping would enable us to obtain unbiased estimates of DEA efficiency scores. Although we conducted a robustness check for the cost efficiency in Chapter 8, in future research bootstrapping allows us to measure the sensitivity of the efficiency scores to the sample variations.

- This study has been based on farms in Wales and England. So, an important question arises if this study can be replicated in other countries in the UK like Scotland and Northern Ireland.
- Currently, UK is going through Brexit. It would be interesting to see the impact Brexit would have on the agricultural sector and what policy changes would be implemented in the dairy sector. Due to Brexit, the UK will no longer be a part of Common Agricultural Policy (CAP) so in future research, we would like to examine how changes in subsidies might affect dairy farm's performance.
- Lastly, we could explore what sustainable intensification means for wider economic development process, especially in the rural economy.

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