Greenhouse gas emissions and the technical efficiency of Alberta dairy farms: What are the trade-offs?

by

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Abstract

The dairy sector is a significant contributor to Canada's economy and the Canadian diet; however, the associated carbon footprint comprises a large portion of agricultural emissions. Anthropogenic greenhouse gas (GHG) emissions are widely accepted as a key contributor to climate change, which is predicted to have negative ecological, social, and economic effects. When considering GHG mitigation from dairy farms, in addition to environmental impact and social license, economic considerations are also necessary for lasting sustainability. The question addressed by this study is: can reducing GHG emissions be compatible with maintaining the technical efficiency of dairy farms in Alberta?

As conventional production functions do not accommodate detrimental outputs, a hyperbolic distance function specification is used for this study. Results from production frontiers estimated with and without considering GHG emissions are compared. For this study, technical efficiency refers to the efficiency derived from the frontier not considering GHGs, while environmental efficiency is estimated from a frontier that includes GHGs as a “bad” output. Efficiency is measured using both stochastic frontier analysis (SFA) and data envelopment analysis (DEA). To see the effect of farm and producer characteristics on efficiency levels, inefficiency models are also estimated.

The results indicate that environmental and technical efficiency estimates are highly correlated, suggesting that the objective of minimizing GHGs aligns with increasing technical efficiency. However, average technical efficiency is high, with many producers close to the frontier, and further reductions in GHGs may come at a cost to producers. This study found the average opportunity cost of foregone milk revenue per

tonne of CO_2 equivalent abated (calculated as a shadow price) is $308.29. It is also seen that increasing milk yield per cow, being in the Southern part of Alberta, and increasing the proportion of forage in the diet is associated with improved environmental efficiency.

Preface

This thesis is an original work by Stephanie Le. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name "An Economic Assessment of Greenhouse Gases and Production Efficiency for Alberta Dairy Farms", No. Pro00062066, March 11th, 2016.

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List of Abbreviations

AAF	Alberta Agriculture and Forestry
AAFC	Agriculture and Agri-Food Canada
ADG	Average Daily Gain
AE	Allocative Efficiency
AFSC	Agriculture Financial Services Corporation
AGR	Above Ground Residue
AVI	Aquifer Vulnerability Index
BGR	Below Ground Residue
CDC	Canadian Dairy Commission
CDIC	Canadian Dairy Information Centre
CRS	Constant Returns to Scale
CH_4	Methane
CO_2	Carbon Dioxide
DEA	Data Envelopment Analysis
EE	Environmental Efficiency
EPA	Environmental Protection Agency
FI	Fisher Price Index
FPCM	Fat and Protein Corrected Milk
GE	Gross Energy
GHG	Greenhouse Gas
IDF	International Dairy Federation
IPCC	Intergovernmental Panel on Climate Change
kg	Kilogram
LI	Laspeyres Index
N_2O	Nitrous Oxide
NE	Net Energy
OMAFRA	Ontario Ministry of Agriculture, Food, and Rural Affairs
PI	Paasche Index
rBST	Recombinant Bovine Somatotropin
RGGI	Regional Greenhouse Gas Initiative
SFA	Stochastic Frontier Analysis
TDN	Total Digestible Nutrients
TE	Technical Efficiency
VRS	Variable Returns to Scale

Chapter 1. Introduction

1.1 Background

Canada's dairy sector comprises a large portion of the agricultural economy, and is an important part of the Canadian diet– over eight billion kilograms (kgs) of milk are produced in Canada annually, resulting in over $6.1 billion dollars in farm cash receipts (CDIC 2017a). However, dairy production has a significant carbon footprint; at the farm level, approximately one kg of carbon dioxide (CO_2) equivalents is released per kg of milk produced in Canada (Vergé et al. 2007), accounting for 20% of greenhouse gas (GHG) emissions from the livestock sector (Vergé et al. 2013). Anthropogenic GHGs are widely accepted as a key contributor to climate change, which is predicted to have negative ecological, social, and economic effects; for example, ocean acidification, spread of diseases and pests, and meteorological issues such as floods and droughts (Haines et al. 2006). As a result, societal concern and consumer demand for products with a low carbon footprint are growing (Forbes et al. 2009). This is especially true for the livestock sector, where the "social license" to farm is highly contingent on consumers' perception of the agri-food industry's ability to produce in an ethical and environmentally friendly manner (de Boer 2012). However, sustainability is often cited as having three pillars– beyond the environmental aspect, social and economic viability are also required for lasting improvements (Hansmann et al. 2012). Thus, for a truly sustainable dairy industry, farming practices that offer fair economic returns for producers, affordable milk prices for social welfare, and minimal environmental degradation, should be considered.

In response to societal concerns, a variety of GHG mitigation initiatives have been introduced by various levels of government. For example, under Alberta's Agricultural Carbon Offset Program, farmers adopting GHG mitigation practices can receive carbon offset credits, which can then be sold on the carbon market (AAF 2015d). In Alberta, the most widely adopted offset protocol is tillage management, which involves adoption of reduced till or no till practices (AAF 2015d). Protocols also exist for beef, dairy, renewable energy generation, and nitrogen efficiency (AAF 2015d). To enhance adoption of GHG mitigation practices, the offset program focuses on protocols that can decrease GHGs while encouraging production; for example, the mitigation areas for the dairy protocol are: increasing milk yield, increasing feed efficiency, retaining fewer heifers, and changing manure management practices (Alberta Environment 2010). From 2007 to 2012, 11 megatonnes of carbon dioxide were registered, resulting in over $130 million in agricultural offsets revenue (AAF 2015d). However, transactions costs (e.g. record keeping, verification) can overwhelm the value of the carbon offsets, especially for smaller projects (AAF 2014).

1.2 Economic Problem

Agricultural GHG emissions are a negative externality; that is, the GHG emissions released in the production of agricultural goods impose a social cost (i.e., climate change) which is not accounted for in production decisions. As a result, there may be an oversupply on the market, which creates market inefficiencies, as the social cost of production exceeds the social benefit derived from the consumption of agricultural products. To bring production down to a socially optimal level, policy intervention may be required; for example, to factor the social cost into production or consumption decisions through taxation, or to restrict production through quotas.

However, identifying effective policy instruments for agricultural GHG mitigation can be a challenge, especially as different sectors may have different responses to the same policy. For example, the conservation cropping protocols for the Alberta Agricultural Offset Program generated the majority of offsets; in contrast, there have been no offsets sold by Alberta dairy farms, even though the dairy protocol was published over seven years ago (AAF 2017a, Alberta Environment 2010). Pannell (2008) suggests that the appropriate policy intervention depends on whether the mitigation strategy is a cost or benefit to private firms versus the public, as well as the magnitude of the effect. For instance, positive incentives should be provided for producers by the government if the project incurs a small private cost for a larger public benefit. Identifying the private cost or benefit of GHG mitigating farming practices is the first step in creating effective agricultural policy to mitigate climate change.

There is a large body of research on GHG mitigation practices that also increase production levels. The most common areas are through increasing milk yield, feed efficiency, and animal health. For example, reductions in the replacement rate, culling rate, and calving interval for dairy cows have been seen to decrease GHG emissions (Weiske et al. 2006). In addition, enteric methane production, which comprises the majority of dairy farm level GHG emissions, represents a loss of energy that could have utilized towards production. Strategies to inhibit methanogens include feeding lipids, more digestible diets, and antimicrobials such as ionophores, nitrates, dicarboxylic acids, and bacteriocins (Cottle and Weidemann 2011). However, GHG mitigation practices that increase production do not necessarily translate to increased economic or environmental sustainability. For example, increasing milk yield per cow decreases enteric methane per kg of milk, but achieving this goal may require a more intensively produced feed or increased labour and management, which raises costs and input use (Boadi et al. 2004).

To provide a more inclusive index of overall farm performance, technical efficiency can be considered, as it is a measure that can encompass the output capacity and resource use of the entire farm. In addition, technical efficiency reflects the producer's ability to produce maximal outputs while minimizing inputs. The question is, how does GHG mitigation affect the efficiency of dairy farms? Many previous studies have examined the technical efficiency of dairy farms (e.g., Cabrera et al. 2010, Cloutier and Rowley 1993, Weersink et al. 1990), using both stochastic frontier analysis (SFA) and data envelopment analysis (DEA). When considering environmental factors in efficiency, earlier studies mainly focused on nitrogen surpluses (e.g., Mamardashvili et al. 2016, Reinhard et al. 1999) and only a small number of technical efficiency studies examine GHGs (e.g., Njuki and Bravo-Ureta 2015, Shortall and Barnes 2013). The uncertainty surrounding the impacts of different farming strategies not only deters adoption of GHG mitigation practices, it also hinders the appropriate policy response. This research proposes to address the gap in knowledge by studying the relationship between farm-level efficiency and whole farm GHG emissions.

1.3 Research Problem and Objectives

The purpose of this research is to evaluate the trade-offs between reducing GHG emissions and the efficiency of dairy production in Alberta. Specifically, the objectives of this study are to:

- Calculate GHG emissions from the entire dairy enterprise at the farm level for Alberta dairy farmers
- Estimate multi-output production frontiers that incorporate desirable and undesirable outputs for Alberta dairy production
- Study the relationships between efficiencies calculated with and without considering environmental impacts
- Identify management practices and farm characteristics correlated with “sustainable” farms
- Estimate the shadow price of GHG emissions; that is, the cost of GHG reduction in terms of foregone milk revenue, for Alberta dairy farms
- Compare the results obtained from SFA and DEA frameworks

As the relationship between GHG emissions and farm-level efficiency is largely unexplored, the results of this study can assist in creating economically viable GHG mitigation policies, aid producer decision making in response to policy initiatives, and provide methodological contributions for the inclusion of a detrimental output in efficiency analysis. Ultimately, the goal is to provide recommendations for policy makers and industry to enhance the sustainability of the dairy industry environmentally, economically, and socially.

1.4 Organization of Thesis

Five chapters follow this introductory chapter. Chapter Two provides an overview of dairy production in Alberta, farm-level GHG emissions, and policy initiatives for livestock GHG mitigation.

Chapter Three outlines the theoretical framework used in the research problem−specifically, the theory behind efficiency analysis and multi-output frontiers, and the existing literature on dairy efficiency and GHG emissions.

Chapters Four and Five discuss stochastic frontier analysis and data envelopment analysis, respectively. The data, methods, and results for each type of analysis are also presented in the chapters. Chapter Six concludes with a discussion of the conclusions, policy implications, limitations, and possible extensions of this research.

Chapter 2. Background

This chapter provides the background information relevant to the objectives of this study. First, an overview of dairy production in Alberta is provided, followed by a discussion of key sources of agricultural GHG emissions. Next, GHG mitigation strategies for dairy farms are summarized, and the chapter concludes with policy initiatives for GHG mitigation.

2.1 Dairy Production in Alberta

2.1.1 Overview of Alberta dairy farms

In Canada, the dairy sector comprises 10.1% of total farm cash receipts and 25.5% of cash receipts from livestock farms (Statistics Canada 2017a). In Alberta, where the agricultural sector is dominated by the beef industry, dairy farms comprise 4.1% of total farms and 9.1% of livestock farms (Statistics Canada 2017a). Considered either provincially in Alberta or nationally, dairy is the second largest livestock industry, with cattle being the largest and hogs being third (Statistics Canada 2017a).

The majority of dairy production is concentrated in Ontario and Quebec. These two provinces account for 68.6% of total national dairy farm cash receipts (AAFC 2017). In 2015, Alberta dairy farms generated over $540 million in dairy farm cash receipts to make up 9.0% of the national total (AAFC 2017). However, Alberta only had 4.7% of the dairy farms in Canada, and the discrepancy between the number of farms and the amount received in farm cash receipts can be explained by the larger herd sizes in Alberta, where the average is 142 head, compared to the national average of 82 head (AAFC 2017). Looking at the historical trends, the dairy sector is following the pattern common to most agricultural sectors in Canada where total production is increasing, number of farms is decreasing, and average farm size is increasing (Figures 2.1 and 2.2). Other trends include an increasing number of organic dairy farms in Alberta, where almost 10 million litres of organic milk were produced from ten farms in 2012 (AAFC 2012), up from two farms producing 400,000 litres of milk in 2007 (Canadian Organic Growers 2010), and the automation of dairy operations through technology such as rotary parlours and robotic milking (CDC 2017a).

Dairy farms in Canada are highly specialized, with the majority of revenue per farm being derived from milk and dairy cattle sales (CDC 2017a). The most common dairy breed in Canada is Holstein, representing 93.9% of all dairy cows (AAFC 2017). This is followed by Jerseys at 3.1%, and Ayshires at 2.1% (AAFC 2017). On average, dairy cows in Canada are milked two to three times per day and produce around 30 litres of milk per day (BCSPCA 2017). In Canada, dairy cows typically lactate for approximately 305 days, and spend 60 days in a "dry period" to prepare for parturition (BCSPCA 2017). After calving, lactation begins, and the cows are impregnated again following an interval of 60 to 90 days, most commonly by artificial insemination, after which a gestation period around 280 days follows (BCSPCA 2017). Typically, calves are separated from the cow within 24 hours of birth, where the non-replacement female calves and the male calves are eventually sold for beef (BCSPCA 2017). Heifers are bred at approximately 16 months of age and have their first calf around two years of age (BCSPCA 2017). Cows are typically culled at around 5 years of age, at an average of approximately 2.5 lactation cycles (Alberta Milk 2017a, BCSPCA 2017).

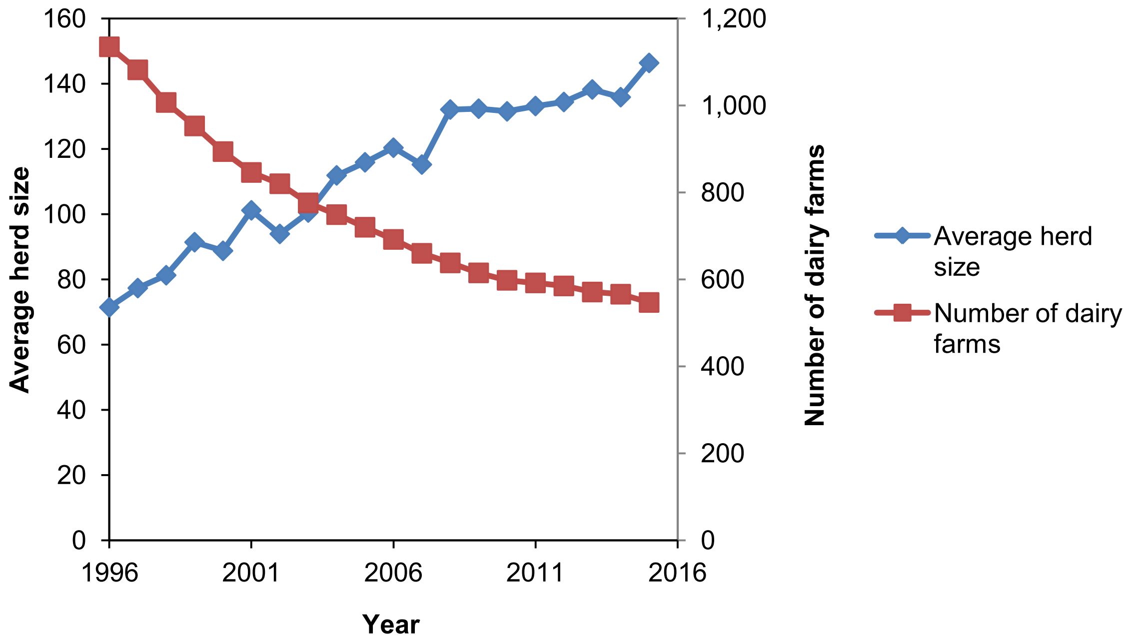

Figure 2.1 Average herd size and number of dairy farms in Alberta (1996-2015)

Source: CDIC 2017c, Alberta Agriculture and Forestry Dairy Cost Study

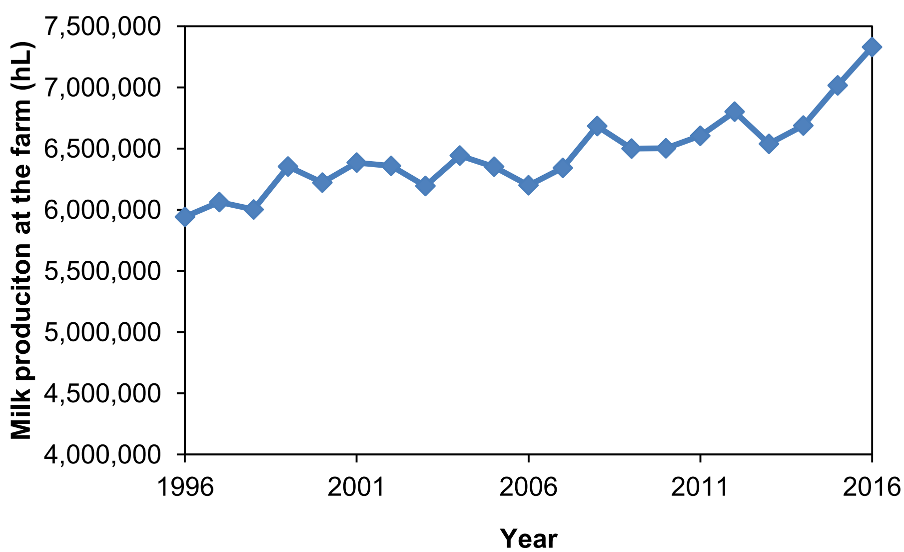

Figure 2.2 Total annual milk output of Alberta dairy farms (1996-2016)

Source: CDIC 2017b

In terms of management, dairy barns in Alberta predominantly have a free-stall configuration, and approximately half of the producers use liquid manure storage while the other half use solid storage (Wallace and Landiak 2013). Pasturing is not a common practice in Alberta, and dairy cows are fed a ration consisting of a mixture of forage and concentrate (Alberta Milk 2017b). Forage comprises 50 to 60 percent of a dairy ration where typical forages are hay and silage; in Alberta, grass and alfalfa hay, as well as barley, corn, and alfalfa silage are common (Alberta Milk 2017b). Concentrate consists of grain, protein, fat, and mineral and vitamins. In Alberta, typical grains used in dairy rations are barley, corn, oats, and wheat, and common protein sources are canola meal, distillers grains, soybean meal, and corn gluten meal (Alberta Milk 2017b).

2.1.2 Supply management of the dairy industry

In Canada, supply management, where producers must hold quota to market their products, applies to five industries– dairy, chicken, turkey, table eggs, and hatching eggs (Heminthavong 2015). In the 1970s, to address the volatility in milk prices, milk supply, and producer and processor revenues, dairy became the first commodity to have national supply management (CDC 2017b). In a supply managed industry, the national production level is set to forecasts of demand to avoid shortages or surpluses, as well as to create a stable environment for farmers (CDC 2017b). However, some concerns regarding supply management include higher consumer prices, barriers to trade, reduced choice in dairy products due to limited imports, reduced incentives to innovate, and barriers to entry for new farmers due to the high price of quota (Findlay 2012).

There are three pillars to supply management. The first is production control, where a national production level and production quotas for each province are set by each commodity's national agency. The provincial boards then administer quota to member farmers, who incur penalties if their production levels do not fall within their allocated quota. The second pillar is pricing mechanism where producers are guaranteed a minimum price based on the cost of production and current market conditions. Prices are negotiated with processors by the provincial boards. The third pillar is import control where imports of supply managed commodities are restricted by tariff rate quotas to protect the domestic market (Heminthavong 2015).

Milk is divided into two main types– fluid milk, which is milk intended for use in producing beverages, and industrial milk, which is milk that undergoes further processing to produce products such as butter and cheese. In Canada, 39% of milk is used for fluid milk while 61% is allocated for industrial milk (Mussell 2016). The two main types of milk are further divided into a total of 19 subclasses of milk types, and milk is sold to processors based on these classes as well as on the milk components (CDC 2016). Quota is measured in terms of butterfat levels regardless of end-product usage of milk; as such, producers are paid for their milk based on the blended price across classes for their milk pool (Mussell 2016). There are two milk pools in Canada: the P5 Pool, which includes Ontario, Quebec, New Brunswick, PEI, and Nova Scotia, and the Western Milk Pool which covers BC, Alberta, Saskatchewan, and Manitoba.

The Canadian Dairy Commission, the national agency for dairy supply management, stabilizes market quantity through setting a quota for national industrial milk production as well as through setting support prices for butter and skim milk powder to remove surplus inventory (Heminthavong 2015, Mussell 2016). For market prices, fluid milk price is largely determined by a national fluid price formula which is influenced by the cost of production and the consumer price index (Mussell 2016). For industrial milk, the pricing is directly influenced by the support prices, which are affected by the cost of production measured by the Canadian Dairy Commission (Mussell 2016).

2.2 Agricultural GHG Emissions

2.2.1 Overview of agricultural GHG emissions

Globally, agriculture and land use change (e.g., deforestation) contribute a significant portion of GHG emissions, accounting for one third of the carbon footprint (AAFC 2016). In 2015, Canada emitted a total of 722 megatonnes of CO_2 equivalents, which is 18% higher than the GHG emissions level in 1990 (Environment and Climate Change Canada 2017). The largest proportion of GHG emissions were from the oil and gas sector (26% of total GHG emissions), followed by the transportation sector (24% of emissions) (Environment and Climate Change Canada 2017). Agriculture was responsible for 10.1% of total GHG emissions at 72.8 megatonnes of CO_2 equivalents (Environment and Climate Change Canada 2017). Out of these emissions, 22 megatonnes were from agricultural production in Alberta. Of these, 44% were from enteric fermentation, 10% from manure, 32% from soils, and 14% from fuel use (AAF 2017b). Of the total Canadian agricultural emissions, 37 megatonnes were from livestock, with beef responsible for 70.2% of livestock emissions, followed by dairy (15.1%), and swine (8.4%) (Environment Canada 2015).

The main sources of agricultural GHGs are carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (NO_2) (AAFC 2016). These gases differ in their global warming potential; that is, their ability to trap heat in the atmosphere. CH_4 is almost 20 times more potent than CO_2 and NO_2 almost 300 times more effective than CO_2 at trapping heat (AAFC 2016). Out of all the agricultural GHG emissions, over 95% are CH_4 and NO_2 (Environment Canada 2015). CO_2 is released from soil cultivation, electricity use, and fuel combustion; CH_4 from enteric digestion and manure decomposition; and NO_2 is given off from the degradation of fertilizer, manure, and crop residue (AAFC 2016). Agriculture can also act as a carbon sink as carbon can be sequestered in soil organic matter and perennial vegetation (AAFC 2016). The emission or absorption of CO_2 from agricultural soils depends on the net effect of the storage of carbon in organic matter versus its release in the decomposition of organic matter (AAFC 2016).

Trends in GHG emissions in Alberta can also be seen. Livestock methane emissions have been decreasing since 2005 due to lower herd sizes from increased efficiency while NO_2 emissions have increased due to increased fertilizer use for higher yielding crops (AAF 2017b). CO_2 emissions from Alberta farms have gone up due to higher fuel use from increased cropping area, and the sequestration of carbon into soil organic matter has stabilized due to the widespread adoption of cropping conservation practices (AAF 2017b).

2.2.2 GHG emissions from dairy farms and potential mitigation avenues

In North America, 80% of emissions from the dairy industry are emitted pre-farm gate (Gerber et al. 2010a). Researchers found a GHG intensity of approximately 1 kg

CO_2 equivalent per kg of milk produced in Canada at the farm level (McGeough et al. 2012, Vergé et al. 2007). Sources of GHG emissions from a dairy farm are illustrated in Figure 2.3, and it includes CH_4 from enteric fermentation and manure; N_2O from soil, crop residue, manure, and fertilizer; and CO_2 from soil, fuel, on-farm energy use, and the energy used to produce farm inputs. As excess manure can displace the use of synthetic fertilizer, manure can generate a potential carbon offset, as seen in the diagram.

Previous Canadian studies have determined that methane comprises the largest proportion of GHGs emitted before the farm gate, ranging from 43-56% of total emissions in terms of CO_2 equivalents (McGeough et al. 2012, Vergé et al. 2007). Enteric methane accounted for 78-86% of total methane, with the remainder comprised of manure methane emissions (McGeough et al. 2012, Vergé et al. 2007). Nitrous oxide contributed 32-40% of total emissions, and CO_2 emissions 4-25% (McGeough et al. 2012, Vergé et al. 2007). For N_2O emissions from dairy farms in the prairie provinces, Vergé et al. (2007) found that 28% were from synthetic fertilizer use, 40% from manure, 19% from indirect nitrogen volatilization and leaching, and 13% from crop residue. For CO_2 from energy use, 40% was from fertilizer production, 28% from field work, 20% from machinery, and 12% from electricity use (Vergé et al. 2007). While electricity is only a small proportion of total dairy farm GHG emissions, the dairy industry uses more electricity than any other agricultural commodity in Canada (Vergé et al. 2007).

Both McGeough et al. (2012) and Vergé et al. (2007) found enteric methane to comprise almost 50% of total farm emissions in terms of CO_2 equivalents. Differences were found in the second and third largest proportions where McGeough et al. (2012)

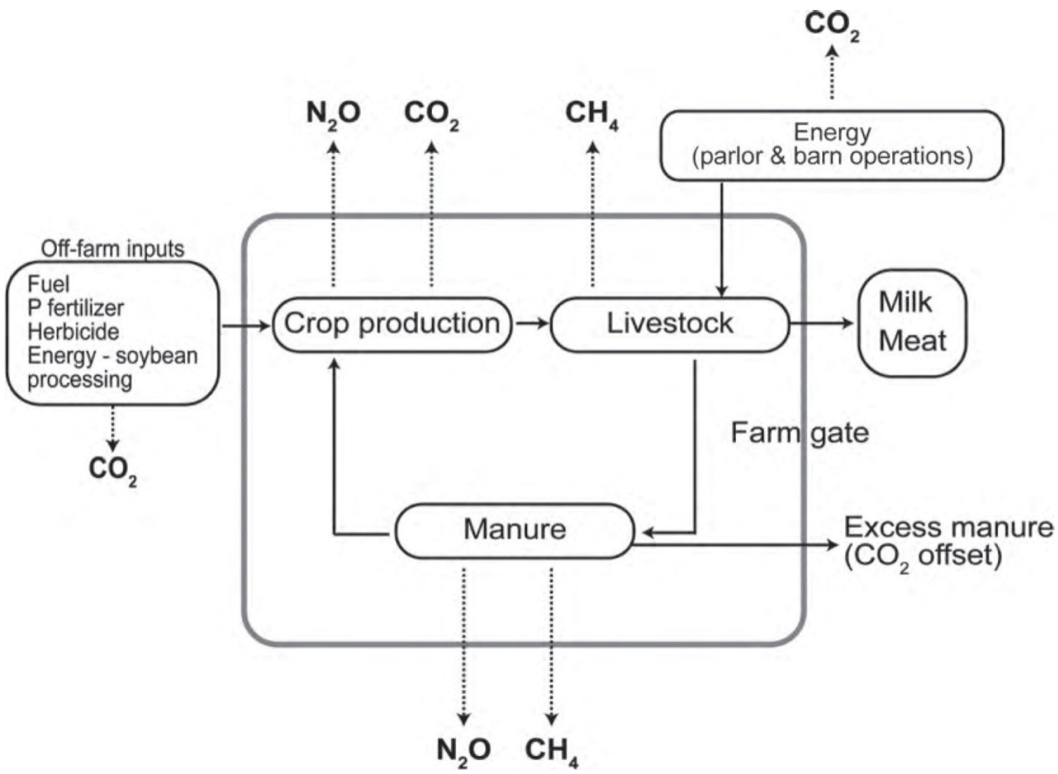

Figure 2.3 GHG emissions from a typical Canadian dairy farm
Source: McGeough et al. 2012, pp. 5169, Figure 2

estimated soil emissions to be 30% of total emissions and manure emissions to be 15%, while Vergé et al. (2007) found the reverse to be true with soil at 30% and manure at 15%. Of the GHG emissions, McGeough et al.'s (2012) life cycle assessment found that 64% were from lactating animals, 20% were from dry cows and pregnant heifers, and 10% were from animals under one year of age, with similar findings by Vergé et al. (2007).

From the various sources of dairy farm GHG emissions, much research has been conducted on GHG mitigation practices for dairy farms, with the main areas being feed, manure, animal health, and production. Feed management primarily targets enteric methane production, the largest contributor to dairy farm GHG emissions. Enteric methane is produced predominantly from the fermentation of feed by methanogens in the rumen of the cow (Boadi et al. 2004). Enteric methane mitigation is a well-researched area, and established mitigation strategies for farm applications include the use of ionophores, lipids, higher forage quality, and increased use of grain (Boadi et al. 2004). For example, monensin (an ionophore) can reduce enteric methane by 20% when fed to dairy cattle (Sauer et al. 1998). These strategies reduce enteric methane through inhibiting methanogens or diverting hydrogen ions from methanogens (Boadi et al. 2004).

Newer strategies in recent research include defaunation, probiotics, acetogens, bacteriocins, bacteriophages, vaccination against methanogens, organic acids, essential oils, immunization, genomic selection for lower methane cows, and enzymes (Boadi et al. 2004, Grainger and Beauchemin 2011). In Hristov et al.'s (2013) extensive review, recommended feed management practices for GHG mitigation include feeding tannins, lipids, an increased proportion of grain, higher quality forage, and processed feeds. Practices that were not recommended due to having a low effect, a detrimental effect on the animal, or insufficient research include saponins, essential oils, exogenous enzymes, defaunation, and methanogen inhibitors such as chloroform (Hristov et al. 2013). Recommendations for dairy farmers to reduce GHGs using feed management from the Alberta government include: genetic selection to increase feed efficiency, adding grain to the diet, improving forage quality, matching the diet to the nutritional requirements of individual animals, feeding silage rather than dry feed, including lipids at up to 6% of the diet, and processing low quality feed (AAF 2017b).

There are also many mitigation areas for manure emissions. Not only are manure emissions a large proportion of dairy farm GHG emissions, much feed nutrients are also retained in manure. For example, only one third of nitrogen in feed is converted to the protein contained in animal products while the rest is excreted in urine and manure (Kirchgessner et al. 1994). As such, energy in manure biogas can be utilized for electricity production rather than released into the atmosphere. Weiske et al. (2006) estimated that the carbon footprint of dairy farms in Europe can be reduced by 96% if all the manure biogas was used to replace fossil fuels for electricity generation. Manure application techniques can also affect GHG emissions– Weiske et al. (2006) found that compared to broadcasting, manure application by injection or by trail hose can reduce dairy farm GHG emissions through reduced nitrogen volatilization, reduced nitrate leaching, and increased nitrogen available for crops to increase yield. Recommended manure management practices include reduction of dietary protein, solids separation, manure acidification, testing the soil and manure to match application rates to crop needs, and avoiding application during the late fall and winter and when the weather is hot, windy, or rainy (AAF 2017b, Hristov et al. 2013).

For GHG reduction through animal management, general strategies include increasing productivity and animal health, reducing days before puberty, reducing days on feed, and selecting genetically for fertility (Hristov et al. 2013). Weiske et al.'s (2006) simulation found that reducing the replacement rate (i.e., the proportion of cows removed from the herd each year) of dairy cows from 40% to 30% in conjunction with selling surplus heifers as newborns can reduce GHG emissions by up to 13%. Improving overall production per animal can also decrease GHG emissions. Gerber et al. (2011) found that increasing milk yield per cow will result in higher GHG emissions per cow while decreasing GHG emissions per kilogram of fat corrected milk. In Canada, milk production per cow has increased by 10% over the past five years while the national dairy herd has decreased in number, leading to a decline of GHG emissions with a simultaneous increase in milk production levels (CDC 2017a, Environment Canada 2015). One potential method to increase milk yield is through production enhancing agents; for example, recombinant bovine somatotropin (rBST) can increase milk production by 10-20%, leading to an estimated reduction in enteric methane by 10% (Johnson et al. 1996). When reductions in replacement heifers and feed use are also included, Capper et al.'s (2008) simulation predicts a GHG reduction of 1.0 tonnes of CO_2 equivalents per cow per year if rBST is used. However, there are potential health risks to dairy cattle associated with rBST use and it is not approved for use in Canada (Boadi et al. 2004).

Effective mitigation will likely be a multi-pronged whole-farm approach– Weiske et al. (2006) cautions against focusing on individual GHG sources or farm compartments for mitigation. For example, a natural crust cover on manure storage can reduce CH_4 emissions but increase N_2O emissions, and feeding grain can reduce enteric CH_4 but increase cropping emissions (Boadi et al. 2004, Hristov et al. 2013). Many strategies appear to have potential for reducing emissions; for example, manure scraping to reduce nitrogen volatilization. However, when tested in real applications, the GHG mitigation often becomes minimal. For example, the electricity required for manure scrapers and the additional GHG from prolonged manure storage leads to higher overall farm emissions (Weiske et al. 2006).

Besides the effect on whole-farm GHG emissions, another important consideration in adoption of mitigation practices is the effect on profitability, as that is a key factor affecting adoption by farmers. There is great potential for alignment of GHG mitigation and farm profitability. Enteric methane and excreted nitrogen represent losses in energy and protein, respectively, that could potentially be utilized for production (McGeough et al. 2012). For example, up to 12% of the gross energy intake of cattle is converted to enteric methane (Johnson and Johnson 1995). However, more efficient animals may cost more to purchase as well as to maintain in terms of feed and management.

There can also be high costs associated with many of the mitigation strategies mentioned above; for example, manure biodigesters have significant upfront capital costs where the payback period on the investment can exceed ten years (EPA 2012). Even for practices highly recommended by multiple sources such as feeding more grain, the increased use of grain results in a higher need for nitrogen fertilizer and farm machinery, which not only increases feed expenses, but can also potentially increase overall GHG emissions through higher N_2O emissions and energy CO_2 (Boadi et al. 2004). In addition, levels of fat and grain in dairy rations in North America are already very high and additional increases have limited potential to reduce GHG emissions (Lee and Sumner 2014).

One possible alternative may be the use of high quality forages, which are cheaper than grain and less fuel intensive to farm, leading potentially to lower costs and net reductions in farm GHG emissions (Johnson et al. 1996). Other mitigation practices estimated to increase profitability are reducing the replacement rate, improving the genetic merit of cows, and selling surplus heifers as newborns (Beukes et al. 2010, Weiske et al. 2006). Beyond considering the impact on whole farm GHG emissions and monetary expenses, the social acceptability of the mitigation practices is another important factor; for example, due to rising concerns regarding the use of antibiotic feed additives and hormones in livestock production, the negative public perceptions of ionophores and rBST may lead to poor consumer demand (Boadi et al. 2004). Overall, there has been abundant research on GHG mitigation strategies, but ongoing research, as well as government intervention, is still needed to help align abatement technologies, farmer incentives, and consumer preferences.

2.2.3 Policy initiatives targeting livestock GHG emissions

The basic premise of GHG mitigation policies is to reduce the negative externalities associated with GHG emissions (i.e., effects of global warming). Agricultural GHG emissions are a case of "tragedy of the commons", where the release of GHGs in the atmosphere is free and unrestricted for livestock production but the cost is shared by everyone (Gerber et al. 2010b). Two key types of GHG mitigation policy instruments are market-based mechanisms such as tax, subsidy, and cap and trade regimes; and command and control policies, which are standards or regulations proscribing certain activities (Gerber et al. 2010b). A direct tax on emissions will give producers an incentive to reduce emissions; however, the difficulty in measuring livestock GHG emissions is a major obstacle in its implementation (Gerber et al. 2010b). As such, output can be used as a proxy. Wirsenius et al.'s (2011) study estimated that a tax on livestock products at 60 € per tonne of CO_2 equivalent will reduce GHG emissions by 7%. A per unit tax on output will have low administrative costs, but it will increase commodity prices, raising potential food security concerns (Gerber et al. 2010b, Key and Tallard 2012). While consumption and production will shift to products with a lower carbon footprint, a tax on output does not reward individual producers who pollute less, and there is no incentive for producers to reduce their per unit emissions (Gerber et al. 2010b). Internationally, there are many instances of carbon taxes– for example, Canada, USA, and Europe; however, agricultural GHGs have been excluded in all cases of carbon taxation (Gerber et al. 2010b, Cooper et al. 2013). While Sweden had a tax on a polluting input– a tax on synthetic fertilizers estimated to reduce agricultural GHGs by 2%, it was abolished in 2010 (Mohlin 2013).

Another policy option is the use of subsidies. As farm level emissions are difficult to measure, subsidies given to farmers whose levels of emissions are less than a certain limit are currently infeasible, and output may have to be used as a proxy (Gerber et al. 2010b). Similar to a tax, subsidies can be provided on a per unit of output basis, per unit of output linked to use of certain technology, or based on adoption of the technology itself. For technology-based taxes or subsidies, an incentive to adopt cleaner technology will be present; however, the incentive will be limited to technologies or inputs that are covered by the scheme. Furthermore, technologies that are difficult to monitor and verify are not feasible to include (Gerber et al. 2010b). In addition, subsidies reduce average costs for farmers, which may lead to an increase in production, potentially resulting in higher sectoral GHG emissions overall (Gerber et al. 2010b).

Applications of technology subsidies have been seen in many countries, particularly for biogas digesters. For example, Ontario has a Biogas Systems Financial Assistance Program for farms, California provides cost share funding for installing digesters through the Dairy Power Production Program, Germany subsidizes biomass electricity from agriculture and adoption of biogas systems through the German Agricultural Investment Assistance Program and the Renewable Energies Act, and China has a territorial network on biodigester development and implementation (Gerber et al. 2010b, OMAFRA 2016). Similar to a subsidy, low interest loans or tax breaks can also be given for GHG mitigating practices; for example, Brazil's Low Carbon Agriculture program supports sustainable practices through low income loans (Bustamante et al. 2014).

For cap and trade regimes, also known as emissions trading schemes (ETS), producers are assigned an emissions cap. If their emissions are below the cap, the scheme acts as a subsidy where producers can sell their permits, whereas if they are above the cap, it acts as a tax where producers must purchase permits (Gerber et al. 2010b). As the cost of measuring GHG emissions at the farm level is prohibitive, a feasible ETS may be one where permits are based on output levels or technology use; however, this has the same issues as mentioned above (Gerber et al. 2010b). Due to difficulty in measuring GHGs, political opposition from farmers, and the lack of feasible technology for GHG mitigation from livestock, agriculture has typically been left out of ETS (Gerber et al. 2010b, Smellie 2017). However, New Zealand is likely to become to first country, with plans to include agricultural GHGs in its ETS by 2020 (Smellie 2017).

Related to ETS are carbon offset programs, which allow farmers who reduce emissions to sell carbon offsets on the carbon market. The offset program is similar to a subsidy, and has similar problems such as potential overproduction (Gerber et al. 2010b). Necessary to offset programs are documentation of baseline emissions, verification of the change in practices that would lead to emissions reductions, and establishment of quantification protocols that delineate how many offset credits are generated from changing management practices (Alberta Environment 2010, Gerber et al. 2010b). Agricultural carbon offsets for livestock GHG mitigation have been seen globally; for example, the Alberta Agricultural Offset Program in Canada, the Regional Greenhouse Gas Initiative across various states in the USA, and the New South Wales Greenhouse Gas Reduction Scheme in Australia (AAF 2015d, Gerber et al. 2010b, RGGI 2017).

For dairy production, the Alberta Agricultural Offset Program focuses on practices that can improve production. The four main areas are: higher milk production (e.g., better genetics or husbandry to increase milk yield with less feed), retaining fewer heifers, increased feed efficiency (e.g., higher quality feed or supplements to reduce enteric methane), and changes in manure management (e.g., less storage during warm months) (Alberta Environment 2010). Despite the fact that the practices can improve production, there has been no uptake of the program by dairy farmers as of 2017 (AAF 2017a). One possible reason may be high transaction costs. For example, records to track the baseline emissions of the farm must be kept for three years before any mitigation projects can be undertaken (Alberta Environment 2010).

Command and control policies can include requirements for specific production technologies or standards for maximum emissions levels (Gerber et al. 2010b). Aside from measuring methane emissions from manure storage, the high cost of measuring farm level emissions makes standards for maximum emissions levels infeasible (Gerber et al. 2010b). Generally, command and control policies are less efficient than market-based mechanisms as the same standard is imposed on all producers, especially if the cost of mitigation between individual producers varies widely (Gerber et al. 2010b). In addition, there is no incentive for producers to reduce emissions or to develop cleaner technologies beyond the standard (Gerber et al. 2010b). However, the administrative costs for the government to impose command and control policies are generally less than market-based mechanisms; for example, monitoring the inclusion of a GHG mitigating feed additive for individual producers is more costly than imposing a standard on all feed manufacturers to include the additive (Gerber et al. 2010b).

There has yet to be any command and control policies specific to livestock GHG emissions (Cooper et al. 2013). However, there has been indirect GHG mitigation through other environmental regulations. For example, manure GHGs in Denmark have declined due to restrictions on manure storage and spreading from the Ammonia Action Plan (Gerber et al. 2010b). Another form of command and control GHG mitigation policy can be at the consumer level; for example, mandating carbon labeling of livestock products, which allows consumers to provide incentive through their demand. Another example of targeting GHGs through the consumer level is Sweden, where the national food guide has recommendations on environmentally friendly food consumption; for instance, eating livestock products that are locally produced and from grazing animals (Sweden National Food Agency 2017).

The main barriers to effective policy implementation are the high costs in measuring GHG emissions at the farm level and the lack of feasible technologies. As such, government support for more research in this area would accelerate the use of market-based mechanisms for livestock GHG mitigation. Many national research programs are present; for example, the Agricultural Greenhouse Gases Program in Canada funds research projects to develop GHG mitigation technologies and practices (Government of Canada 2017), and the Livestock Emissions and Abatement Research Network in New Zealand focuses on developing livestock GHG mitigating practices through international scientific cooperation (LEARN 2017). Another challenge regarding livestock GHG policy is a need to be flexible due to a large number of livestock producers owning a small number of animals, diversity of farming styles, and variation across agro-ecosystems (Gerber et al. 2010b). There may also be political opposition to livestock GHG policy– from producer groups or industry if the production costs increase, or from consumer groups if food prices increase or if there is low acceptance of new technologies (for example, feed additives) (Gerber et al. 2010b, Kerr 2016).

For policies to be feasible, they should have limited administrative costs for government as well as limited transactions costs on producers (Gerber et al. 2010b). Administrative costs depend highly on the cost of measuring emissions, verifying compliance, and enforcing policy for livestock operations (Gerber et al. 2010b). Transactions costs include record keeping and registering emissions. Policies that involve large transactions costs, such as carbon offset programs, can be infeasible for small operations (FAO 2009). Key and Tallard (2012) recommend focusing on sector based rather than farm level emissions to circumvent the high administrative and transaction costs. However, sectoral policies do not provide direct incentives for individual farms to reduce emissions. As livestock products are traded internationally, another challenge for effective livestock GHG policy in a global sense is emissions leakage. With policies such as taxes or cap and trade, cost of production can increase in the regulated region, shifting livestock production to unregulated regions, undoing the GHG reductions from the regulation (Gerber et al. 2010b).

There is great potential to reduce GHG emissions from livestock production; however, achieving this potential requires both national and international efforts on researching, developing, diffusing, and implementing new mitigation technologies, as well as improving abilities to monitor, report, and verify emissions from livestock (Gerber et al. 2010b). The government has many tools to address livestock GHG emissions– market-based mechanisms, command and control policies, information and management tools, research investment, technology diffusion, and voluntary compliance programs (Gupta et al. 2007). The most common policy measures for livestock GHG emissions have been subsidies, grants, tax incentives, and carbon offset programs, and the predicted effect of these policies have been small (Cooper et al. 2013). Information and extension programs from government, in addition to a clear price signal, is needed for large scale adoption of GHG mitigation practices by producers (Cooper et al. 2013).

2.3 Chapter Summary

This chapter reviewed the background on the dairy industry in Alberta, sources of and mitigation methods for greenhouse gas emissions from dairy farms, as well as the policy tools available for livestock GHG mitigation. The importance of considering emissions from the whole farm rather than specific farm areas is emphasized because, due to the complexity of the dairy farm, reductions in one area of the farm may lead to higher emissions in another. Furthermore, economic and social considerations are important in the adoptability of a mitigation practice. Government intervention in this area is heavily dependent on measuring GHG emissions in a cost effective manner and successfully aligning producer incentives with GHG abatement. This study primarily focuses on GHG emissions and how it affects the efficiency of dairy farms in Alberta. As efficiency, maximizing output given inputs, generally aligns with firm objectives, the analysis can reveal whether GHG reduction is in line with farmer incentives. The results from this study can contribute to the understanding behind the impact of GHG reduction on producers, assisting with the selection of policy instruments to encourage adoption of GHG mitigating practices.

Chapter 3. Theory and Literature Review

Chapter Three provides the theoretical basis for this study. It begins with a summary of production functions. Next, an overview of multi-output production frontiers is given; specifically, distance functions are explored. The concept of efficiency, including the different types of efficiency (i.e., economic, technical, and allocative), is then introduced, followed by a discussion of considerations in efficiency analysis; for example, deterministic or stochastic measures of efficiency, efficiency with a detrimental output, and factors that affect efficiency. The chapter concludes with a review of relevant literature on dairy efficiency with and without considering detrimental outputs to give an idea of results, methodologies, and remaining gaps in this research area.

3.1 Production Frontiers

A production function relates quantity of output produced to the quantities of inputs used in the production process. A production frontier is the outer envelope of the production function that describes the maximum feasible output from the inputs given the state of technology. They can be described:

$$y = f(\boldsymbol{x}) \tag{3.1}$$

where y represents output and $\boldsymbol{x}$ is a vector of inputs.

There are four key properties associated with production functions (Chambers 1988):

1. Non-negativity: The value of $f(\boldsymbol{x})$ is a non-negative real number
2. Weak essentiality: Positive values of at least one input are required to produce output
3. Monotonicity: Increasing input(s) will not decrease output

4. Concavity: For two input vectors $\boldsymbol{x}^0$ and $\boldsymbol{x}^1$, $f(\theta\boldsymbol{x}^0 + (1-\theta\boldsymbol{x}^1) \geq \theta f(\boldsymbol{x}^0) + (1-\theta)f(\boldsymbol{x}^1)$. If the production function is continuously differentiable, this property is reflected in the non-increasing marginal products of the inputs.

3.2 Multi-Output Production and Distance Functions

The typical production function represented in Equation 3.1 only accommodates one output (i.e., y is a scalar). When there are multiple outputs, the production function can be generalized into a transformation function, with similar properties to those of a production function:

$$T(\boldsymbol{x}, \boldsymbol{y}) = 0 \tag{3.2}$$

where $\boldsymbol{y}$ and $\boldsymbol{x}$ are vectors of outputs and inputs, respectively. Multi-output production can also be represented by a technology set, S:

$$S = \{(\boldsymbol{x}, \boldsymbol{y}) : \boldsymbol{x} \; can \; produce \; \boldsymbol{y}\} \tag{3.3}$$

where S contains all input-output vectors $(\boldsymbol{x}, \boldsymbol{y})$ where $\boldsymbol{x}$ can be transformed into $\boldsymbol{y}$.

To describe multi-output production, distance functions are commonly used. Distance functions were introduced by Debreu (1951), Malmquist (1953), and Shephard (1953, 1970). They can be used without specifying a behavioural objective (e.g., cost minimization or profit maximization), and can be input or output orientated. Input distance functions are typically used when the producer has more control over inputs than outputs, and it considers the maximal proportional contraction of the input vector given an output vector. Output distance functions consider the maximal proportional expansion of the output vector given inputs.

When describing output distance functions, the output set $P(\boldsymbol{x})$, also known as the production possibility set, is first defined:

$$P(\boldsymbol{x}) = \{\boldsymbol{y}\colon \boldsymbol{x}\ can\ produce\ \boldsymbol{y}\} = \{\boldsymbol{y}\colon (\boldsymbol{x}, \boldsymbol{y}) \in S\} \tag{3.4}$$

The output distance function is then represented as:

$$d_o(\boldsymbol{x}, \boldsymbol{y}) = inf\{\delta\colon \frac{y}{\delta} \in P(\boldsymbol{x})\} \tag{3.5}$$

and it follows the following properties, which are derived from the production axioms above: (Coelli et al. 2005)

1. $d_o(\boldsymbol{x}, \boldsymbol{0}) = 0$
2. $d_o(\boldsymbol{x}, \boldsymbol{y})$ is non-decreasing in $\boldsymbol{y}$ and non-increasing in $\boldsymbol{x}$
3. $d_o(\boldsymbol{x}, \boldsymbol{y})$ is linear homogenous in $\boldsymbol{y}$
4. $d_o(\boldsymbol{x}, \boldsymbol{y})$ is quasi-convex in $\boldsymbol{x}$ and convex in $\boldsymbol{y}$
5. if $\boldsymbol{y} \in P(\boldsymbol{x})$ then $d_o(\boldsymbol{x}, \boldsymbol{y}) \leq 1$ where $d_o(\boldsymbol{x}, \boldsymbol{y}) = 1$ if $\boldsymbol{y}$ is on the frontier of the production possibility set

Figure 3.1 illustrates the concept of an output distance function considering two outputs (y_1 and y_2) produced from the input vector $\boldsymbol{x}$**.** For a producer at point *A*, the value of the distance function would be equal to $\delta = 0A/0B$, which is equivalent to the reciprocal of the factor by which all output quantities can be increased for the given level of input(s). As points *B* and *C* are on the production possibility frontier, their distance function value would be equal to one.

For input distance functions, the input set, which is the set of all input vectors that can produce $\boldsymbol{y}$**,** is defined as:

$$L(\boldsymbol{y}) = \{\boldsymbol{x}\colon \boldsymbol{x}\ can\ produce\ \boldsymbol{y}\} = \{\boldsymbol{x}\colon (\boldsymbol{x}, \boldsymbol{y}) \in S\} \tag{3.6}$$

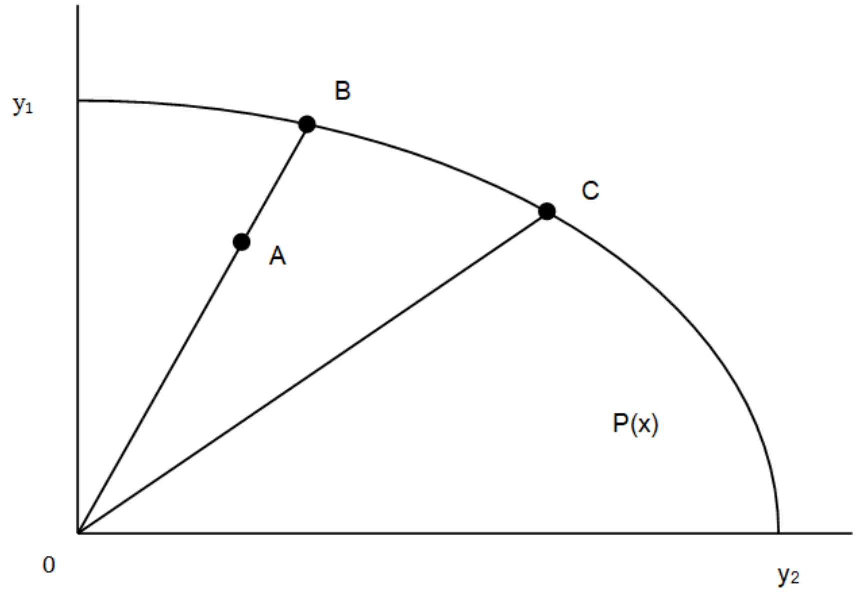

Figure 3.1 Representation of an output distance function

and the input distance function can be represented:

$$d_i(\boldsymbol{x}, \boldsymbol{y}) = sup\{\rho: \frac{x}{\rho} \in L(\boldsymbol{y})\} \tag{3.7}$$

with the following properties similarly derived as for the output distance function:

1. $d_i(\boldsymbol{x}, \boldsymbol{y})$ is non-decreasing in $\boldsymbol{x}$ and non-increasing in $\boldsymbol{y}$
2. $d_i(\boldsymbol{x}, \boldsymbol{y})$ is linear homogenous in $\boldsymbol{x}$
3. $d_i(\boldsymbol{x}, \boldsymbol{y})$ is concave in $\boldsymbol{x}$ and quasi-concave in $\boldsymbol{y}$
4. if $\boldsymbol{x} \in L(\boldsymbol{y})$ then $d_i(\boldsymbol{x}, \boldsymbol{y}) \geq 1$ where $d_i(\boldsymbol{x}, \boldsymbol{y}) = 1$ if $\boldsymbol{x}$ is on the frontier of the input set (i.e. the isoquant)

The input distance function is illustrated in Figure 3.2 where two inputs (x_1 and x_2) are used to produce the output vector $\boldsymbol{y}$**.** The value of the distance function for a producer at point *A* is equivalent to the ratio $\rho = 0A/0B$, which represents the factor by which all inputs can be decreased for the given level of output(s).

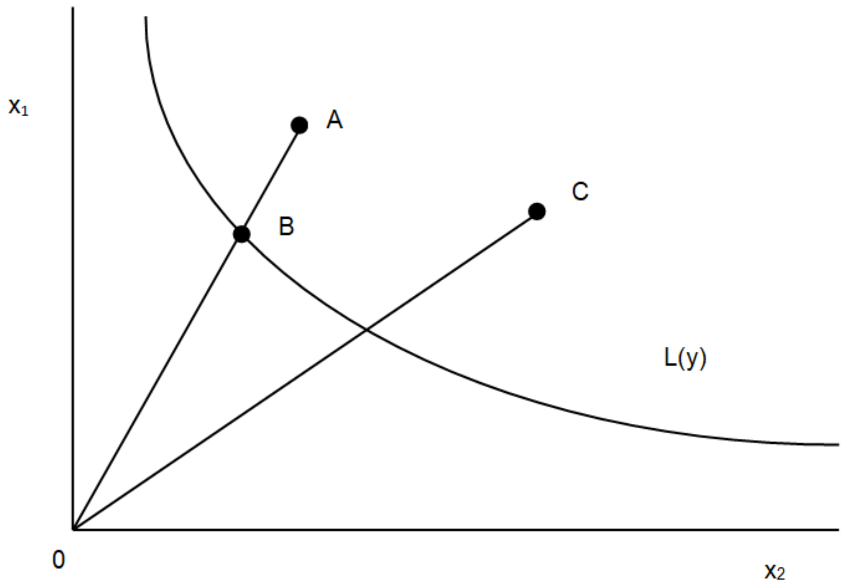

Figure 3.2 Representation of an input distance function

Input and output distance functions are closely related. If $\boldsymbol{y} \in P(\boldsymbol{x})$, it follows that $\boldsymbol{x} \in L(\boldsymbol{y})$. Furthermore, if the technology exhibits constant returns to scale (CRS), the input distance function is the reciprocal of the output distance function: $d_i(\boldsymbol{x}, \boldsymbol{y}) = 1/d_o(\boldsymbol{x}, \boldsymbol{y})$ for all $\boldsymbol{x}$ and $\boldsymbol{y}$.

3.3 Inclusion of a Detrimental Output

Conventional distance functions measure producer performance as the ability to expand all outputs or contract all inputs equiproportionately without discriminating between desirable and undesirable outputs. However, in the presence of a detrimental output (i.e., a by-product of the desirable output that imposes a market or non-market cost), outputs must be treated asymmetrically. The first instance of asymmetric treatment was Färe et al.'s (1985) hyperbolic distance function, which considered the producer's ability to simultaneously expand outputs and contract inputs in an equiproportional manner. Färe et al. (1989) then estimated this distance function non-parametrically to measure environmental performance of paper mills through their ability to expand desirable outputs and contract undesirable outputs. Another distance function that can treat outputs asymmetrically, the directional distance function, was proposed by Chambers et al. (1996). Using linear programming methods, Chung et al. (1997) then used this type of distance function to evaluate the productivity of paper mills considering the expansion of good outputs and contraction of bad outputs.

Both hyperbolic and directional distance functions are useful for studies examining environmental performance as they easily incorporate multiple outputs while simultaneously considering the expansion of good outputs and contraction of bad outputs. Both types of distance functions are dual to the firm's revenue function which allow for calculation of shadow prices (Vardanyan and Noh 2006). The hyperbolic distance function is represented below:

$$D_H(\boldsymbol{x},\boldsymbol{y},\boldsymbol{b}) \ = \ inf\left\{\theta > 0: (\boldsymbol{x},\frac{\boldsymbol{y}}{\theta},\boldsymbol{b}\theta) \in P(\boldsymbol{x})\right\} \tag{3.8}$$

where the distance, or the efficiency, of a producer (D_H) is represented by the scalar θ, and it reflects the ability to expand the desirable output vector ($\boldsymbol{y}$) and contract the undesirable output vector ($\boldsymbol{b}$), given the input vector ($\boldsymbol{x}$) and the production possibility set ($P(\boldsymbol{x})$). With a detrimental output, $P(\boldsymbol{x})$ can be represented:

$$P(\boldsymbol{x}) = \{(\boldsymbol{y},\boldsymbol{b}): \boldsymbol{x}\ can\ produce\ (\boldsymbol{y},\boldsymbol{b})\} = \{(\boldsymbol{y},\boldsymbol{b}): (\boldsymbol{x},\boldsymbol{y},\boldsymbol{b}) \in S\} \tag{3.9}$$

The hyperbolic distance function allows for the asymmetric treatment of beneficial and detrimental outputs by considering equiproportional contraction (expansion) of bad (good) outputs in a multiplicative manner. The enhanced hyperbolic model also considers the proportional contraction of inputs and can be represented by:

$$D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) = \inf\{\theta \geq 0: \left(\boldsymbol{x}\theta, \frac{\boldsymbol{y}}{\theta}, \boldsymbol{b}\theta\right) \in S\} \tag{3.10}$$

The distance ranges from: $0 < D_H(x, y, b) \leq 1$, where a value of 1 represents full technical efficiency. If the customary production function axioms are satisfied by the technology, the hyperbolic distance function has the following properties: (Cuesta et al. 2009)

1. almost homogeneity: $D_H(\mu^{-1}x, \mu y, \mu^{-1}b) = \mu D_H(x, y, b), \mu > 0$
2. non-decreasing in beneficial outputs: $D_H(x, \alpha y, b) \leq D_H(x, y, b), \alpha \in [0,1]$
3. non-increasing in detrimental outputs: $D_H(x, y, \alpha b) \leq D_H(x, y, b), \alpha \geq 1$
4. non-increasing in inputs: $D_H(\alpha x, y, b) \leq D_H(x, y, b), \alpha \geq 1$

Parametrically, almost homogeneity can be imposed through a translog functional form (Vardanyan and Noh 2006).

The directional distance function, represented below, is the additive counterpart to the hyperbolic distance function (Vardanyan and Noh 2006):

$$D_D(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b};\ \boldsymbol{g_y}, -\boldsymbol{g_b}) = sup\{\psi \geq 0: (\boldsymbol{x}, \boldsymbol{y} + \psi\boldsymbol{g_y}, \boldsymbol{b} - \psi\boldsymbol{g_b}) \in P(\boldsymbol{x})\} \tag{3.11}$$

where the distance is represented by the scalar ψ, and the directional vectors ($\boldsymbol{g_y}, \boldsymbol{g_b}$) are determined exogenously. The producer's objective is to expand the desirable output vector by $\psi\boldsymbol{g_y}$ while contracting the undesirable output vector by $\psi\boldsymbol{g_b}$**.** Unlike the hyperbolic distance function, the range of the directional distance is bound by zero on one end and positive infinity on the other, where an efficient producer will have $D_D = 0$ (Vardanyan and Noh 2006). Instead of the almost homogeneity property seen in the hyperbolic distance function, the directional distance function is characterized by the translation property, where if the vector of good outputs is increased by a factor β and the bad outputs decreased by a factor β, then the value of the resulting distance function will decrease by β (i.e. becomes more efficient) (Färe et al. 2005):

$$D_D(\boldsymbol{x}, \boldsymbol{y} + \beta \boldsymbol{g_y}, \boldsymbol{b} - \beta \boldsymbol{g_b};\ \boldsymbol{g_y}, -\boldsymbol{g_b}) = D_D(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b};\ \boldsymbol{g_y}, -\boldsymbol{g_b}) - \beta \tag{3.12}$$

Due to this translation property, a quadratic functional form can be used to represent directional distance functions parametrically (Vardanyan and Noh 2006). Typically, the direction vector is chosen to be $(g_y, -g_b) = (1, -1)$, allowing for equal weighting of desirable and undesirable outputs and increasing the ease of interpretation (Njuki and Bravo-Ureta 2015).

Hyperbolic and directional distance functions result in differently shaped production frontiers and output sets. However, there does not appear to be an obvious superior choice between the two types of distance functions (Vardanyan and Noh 2006). Vardanyan and Noh's (2006) study compared deterministic parametric hyperbolic translog and directional quadratic functions and found that for both forms, the resulting shadow prices did not appropriately resemble the "true price" (proxied by the market price of SO_2 emissions) of the detrimental output. For their study, the quadratic directional function did result in shadow prices more similar to the market price due to better global approximation properties than the translog hyperbolic function. However, one issue with directional distance functions is the specification of direction vectors for the outputs, which can affect the resulting estimates. For example, using different direction vectors can result in highly variable shadow prices (Vardanyan and Noh 2006). Currently, clear guidelines for choosing directional vectors have not been established (Cherchye et al. 2015).

3.4 Concepts in Efficiency

The concept of efficiency used for this study begins with Farrell (1957). Based on the work of Koopmans (1951) and Debreu (1951), Farrell (1957) defined a measure of firm efficiency to account for multiple inputs. Farrell (1957) proposed that economic efficiency is composed of two components– technical and allocative, which are illustrated below. Efficiency can also be measured from an input or output orientation.

Figure 3.3 illustrates Farrell's (1957) efficiency from an input orientation, where x_1 and x_2 are inputs used to produce a single output y. From an input orientation, technical efficiency (TE) reflects the ability of the producer to minimize inputs for a given output. As such, any point on the isoquant, represented by line *SS′*, reflects full technical efficiency; for example, *Q* and *Q′*. Allocative efficiency (AE), in an input orientated context, reflects the ability of the firm to select the optimal proportions of inputs given relative input prices (i.e., market signals). While Q’ represents allocatively efficient production, point Q is allocatively inefficient.

For an allocatively and technically inefficient firm operating at point P, technical efficiency can be measured by *0Q/0P*, which considers the distance from *P* to the technically efficient point *Q* on a ray from the origin, where *QP/0P* represents the percentage by which all inputs can be proportionally reduced without affecting output. Allocative efficiency for point *P* is measured relative to point *R*. Point *R* is not feasible (i.e., lies below the isoquant) but represents an input combination with the same proportions as *P* and the same minimum cost as *Q’* (since it is on the minimum isocost line AA’). Point *P*'s AE can be measured by *0R/0Q*, which considers the corresponding radial distance from the isocost line. One interpretation is that it represents the extra

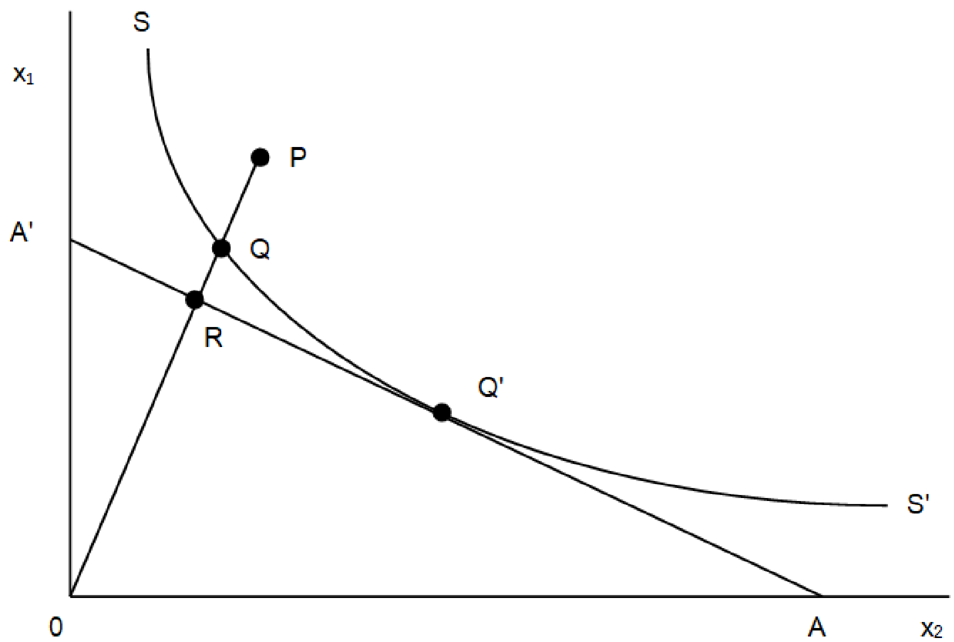

Figure 3.3 Input orientation of efficiency

cost resulting from using non-optimal proportions of inputs. For a producer at point *P*, the level of economic efficiency can be measured by *0R/0P*, which is equal to the product of the technical and allocative efficiency where *0Q/0P* x *0R/0Q* = *0R/0P.*

Efficiency can also be illustrated from an output orientation. Figure 3.4 considers the case where there are two outputs, y_1 and y_2, and a single input. From an output orientation, TE reflects the ability of the producer to maximize output given inputs. Full technical efficiency is seen in any point on the production possibility frontier, represented by line *ZZ'*; for example, *B* and *B'*. AE, in an output orientated context, reflects the ability of the firm to select the optimal proportions of outputs given their prices. In this case, *B'* represents allocatively efficient production, while point *B* is allocatively inefficient.

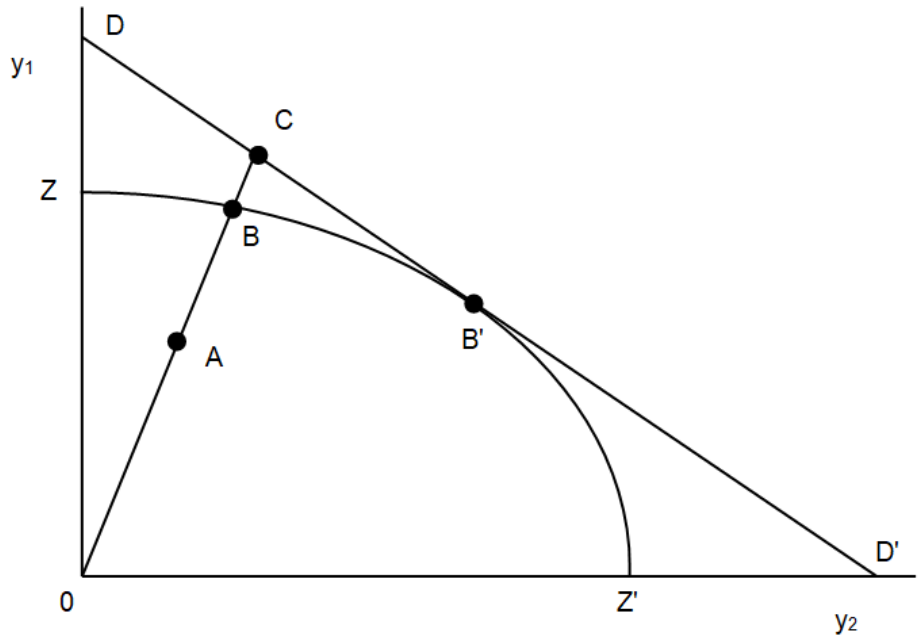

Figure 3.4 Output orientation of efficiency

For an allocatively and technically inefficient firm operating at point *A*, TE can be measured by *0A/0B*, which considers the distance from *A* to the technically efficient point *B* on a ray from the origin, and the percentage by which all outputs can be proportionally increased using the same level of input can be represented by *AB/0B*. Point *A*'s AE is measured relative to point *C*. Point *C* is not feasible (i.e., lies above the production possibility frontier) but represents an output combination with the same proportions as *A* and the same revenue as *B'* (since it is on the maximum isorevenue line *DD*'). As such, point *A*'s AE can be measured by *0B/0C*, which represents the loss in revenue from producing non-optimal proportions of outputs considering the market signals. For a producer at point *A*, the level of economic efficiency can be measured by *0A/0C*, which is equal to the product of the technical and allocative efficiency where *0A/0B* x *0B/0C* = *0A/0C.*

Linking the diagrams from Sections 3.1.2 and 3.1.2 (i.e., Figures 3.1 and 3.4; Figures 3.2 and 3.3), it can be seen that efficiency measures can be derived from distance functions. From an input-orientated distance function, TE can be defined as:

$$TE = \frac{1}{D_i(\boldsymbol{x}, \boldsymbol{y})} \tag{3.13}$$

whereas output orientated TE is defined:

$$TE = D_o(\boldsymbol{x}, \boldsymbol{y}) \tag{3.14}$$

They both exist on a unit interval, and are equivalent to each other under CRS. In addition, these efficiency measures are measured from a ray from the origin, which holds the relative proportions of inputs or outputs constant (Coelli et al. 2005). As such, efficiency becomes a radial measure and does not vary with units of measurement (Coelli et al. 2005).

3.5 Considerations in Efficiency Analysis

3.5.1 Input and output orientated measures of efficiency

The choice of input and output orientated measures of efficiency depends on two main factors– the objective of the producer and the level of control the producer has over different areas of production. Input orientated measures of efficiency may be more appropriate if the producer has more control over the inputs, such as when the outputs are regulated; for example, Coelli and Perelman (2000) used an input distance function to evaluate the efficiency of rail systems. Input orientated measures can also be used if the objective involves minimization (e.g., of cost, detrimental output, input use, etc.); for example, Reinhard and Thijssen (2000) used the assumption of cost and nitrogen minimization to estimate the cost and nitrogen efficiency of Dutch dairy farms. Output orientated measures of efficiency can be considered for cases where the producer has more control over the outputs; for example, Feng and Serletis (2010) used an output distance function to measure the efficiency of the US banking industry. Similarly, for cases where the objective involves maximization (e.g., of production, revenue, etc.) output orientated measures can be an appropriate choice; Cabrera et al. (2010) used a standard production frontier assuming output maximization to estimate technical efficiency of dairy farms in Wisconsin.

3.5.2 Deterministic and stochastic measures of efficiency

Many approaches to measuring efficiency are present in the literature, both deterministic and stochastic. Deterministic frontiers can be parametric or non-parametric, and they attribute all deviations from the frontier to inefficiency. Stochastic frontiers, on the other hand, are parametric, where deviations from the frontier can be due to inefficiency or random noise (Fiorentino et al. 2006). Their differences are illustrated in Figure 3.5 where $f(x;\beta)$ represents the deterministic frontier, *A* and *D* represent inefficient firms, *B* and *E* their corresponding fully efficient points on a deterministic frontier, and *C* and *F* their fully efficient points on a stochastic frontier. For the stochastic frontier, point *C* has a random positive deviation from the deterministic frontier while point *F*'s deviation is negative. A stochastic measure of TE can be represented by *A/C* or *D/F* while a deterministic measure can be represented *A/B* or *D/E.*

The most common non-parametric deterministic approach is data envelopment analysis (DEA), first introduced through Charnes et al. (1978), where linear

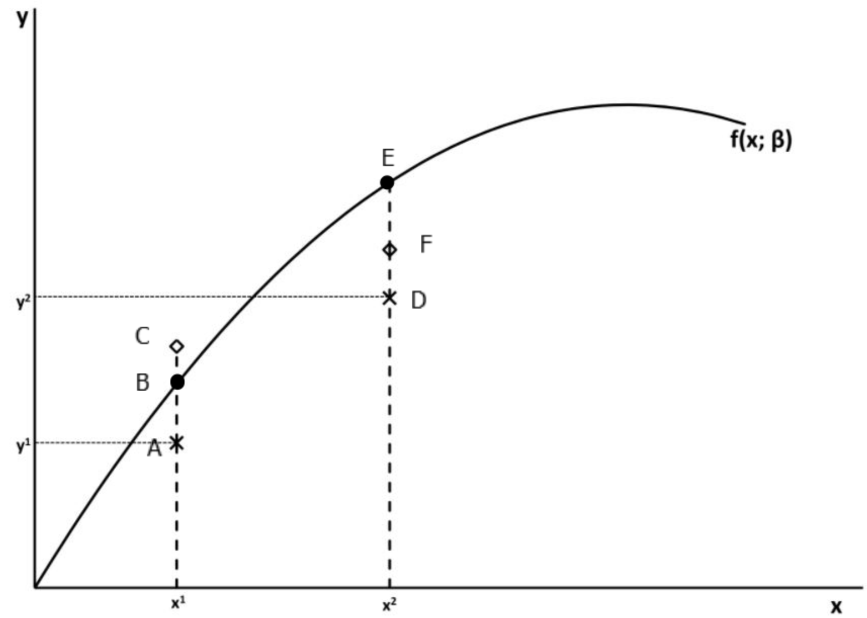

Figure 3.5 Stochastic production frontier

programming methods are used to construct a piece-wise frontier that envelopes the data points. Firm efficiencies are subsequently calculated relative to that frontier (Coelli et al. 2005). An input orientated CRS DEA model, the first type of DEA model to be widely applied, is described below (Coelli et al. 2005):

$$\begin{aligned} & min_{\theta,\lambda}\, \theta, \\ s.t. \quad & -\boldsymbol{y_i} + \boldsymbol{Y\lambda} \geq 0, \\ & \theta \boldsymbol{x_i} - \boldsymbol{X\lambda} \geq 0, \\ & \boldsymbol{\lambda} \geq 0 \end{aligned} \tag{3.15}$$

Assuming there are *N* inputs and *M* outputs for *I* number of firms, $\boldsymbol{x_i}$ and $\boldsymbol{y_i}$ represent column vectors of inputs and outputs for the i^{th} firm, respectively. $\boldsymbol{X}$ is a *N*x*I* matrix representing observed inputs for all *I* firms while $\boldsymbol{Y}$ is a *M*x*I* matrix representing outputs for all *I* firms. θ is a scalar representing technical efficiency and $\boldsymbol{\lambda}$ is a vector of endogenously determined weights where the point ($\boldsymbol{X\lambda}$, $\boldsymbol{Y\lambda}$) represents a point on the piece-wise frontier. Expression 3.15 is solved ***I*** times and a value of θ is obtained for all producers.

If a parametric efficiency model is estimated, the deterministic approach can be expressed:

$$y_i = f(\boldsymbol{x}_i;\ \boldsymbol{\beta})exp(-u_i) \tag{3.16}$$

where y_i is the output of the i^{th} producer, $f(\boldsymbol{x_i};\ \boldsymbol{\beta})$ is the deterministic frontier modeled using a functional form that is suitable for the production technology, $\boldsymbol{x_i}$ is a vector of inputs, $\boldsymbol{\beta}$ is a vector of parameters, and u_i is the non-negative inefficiency term. Expression 3.16 can be estimated using techniques such as corrected ordinary least squares (Winsten 1957), maximum likelihood (Afriat 1972), and modified ordinary least squares (Richmond 1974). From Equation 3.16, TE can be derived:

$$TE = \frac{y_i}{y_i^*} = \frac{f(\boldsymbol{x_i};\ \boldsymbol{\beta})exp(-u_i)}{f(\boldsymbol{x_i};\ \boldsymbol{\beta})} = exp(-u_i) \tag{3.17}$$

where y_i^* is the output of a fully efficient firm on the frontier.

In the case of stochastic frontier analysis (SFA), deviations from the frontier are assumed to be due to a combination of random shocks and producer inefficiency. This model was introduced by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). A stochastic frontier may be represented:

$$y_i = f(\boldsymbol{x_i};\ \boldsymbol{\beta})exp(v_i - u_i) \tag{3.18}$$

With the exception of the stochastic error term v_i, Equation 3.18 is similar to Equation 3.16, and TE is calculated in a similar fashion:

$$TE = \frac{y_i}{y_i^*} = \frac{f(\boldsymbol{x_i};\ \boldsymbol{\beta})exp(v_i - u_i)}{f(\boldsymbol{x_i};\ \boldsymbol{\beta})exp(v_i)} = exp(-u_i) \tag{3.19}$$

There are advantages and disadvantages associated with each approach. For example, a drawback of deterministic approaches is that statistical inferences are not possible without bootstrapping (Simar and Wilson 2007). However, deterministic analysis, at least in the case of DEA, has a smaller data requirement compared to the more computationally demanding SFA (Coelli et al. 2005). SFA may allow for the differentiation between random noise and producer inefficiency. However, with parametric frontiers, the effects of potential misspecification can be confounded with inefficiency (Reinhard et al. 2000). DEA does not impose any assumptions regarding functional form or regarding the distribution of inefficiency, but it cannot account for panel data, whereas this is possible with SFA (Fiorentino et al. 2006). Deterministic frontiers are also more sensitive to outliers (Fiorentino et al. 2006). Both DEA and SFA are used widely in efficiency studies, and due to their different strengths and weaknesses, the model choice is dependent on the trade-offs specific to each study.

3.5.3 Measuring efficiency considering detrimental outputs

This study differs from conventional dairy efficiency studies as it measures technical efficiency with an additional objective of minimizing environmental impact. Conventional efficiency analysis typically only considers one beneficial output. As seen earlier, measuring efficiency with multiple outputs, especially when there are detrimental outputs, is a relatively new field (i.e., the first instance was Färe et al.'s (1989) study) compared to the introduction of efficiency analysis by Farrell (1957). Many strategies to measure efficiency while incorporating undesirable outputs have been proposed by researchers, for both DEA and SFA. Below is a brief overview of different methodologies, as well as some of the challenges associated with each approach.

There are two main approaches to incorporate a detrimental output in DEA– direct, where the structure of the DEA programming rather than the data is transformed, and indirect, where the data are transformed. For the direct approach, one method can be through imposing production axioms to restructure the production possibility curve. Common axioms used in empirical studies include weak disposability where it is assumed that bad outputs can only be reduced with a reduction in good outputs (Färe et al. 1989), or null jointness where the assumption is that it is not possible to produce good output without bad output (Färe and Grosskopf 2004). However, there are issues related to these axioms– they are non-verifiable and it can be difficult to define the production possibility set under these axioms with DEA (Cherchye et al. 2015). Another DEA method under the direct approach is the use of distance functions. Specifically, directional distance functions and hyperbolic distance functions can be used, as they allow for the asymmetric treatment of good and bad outputs (Chambers et al. 1996, Färe et al. 1985). A relatively new method, the by-production approach, has been suggested by Cherchye et al. (2015) and Dakpo et al. (2012). The methodology involves two interdependent frontiers, one for the good outputs and the other for the bad outputs. However, this approach requires the separation of inputs into polluting and non-polluting inputs, which may not be feasible in all cases.

For the indirect approach in a DEA context, the undesirable output is transformed. Most commonly, this can occur through using the negative or reciprocal of the output, or by treating the output as an input (Scheel 2001). Another way of transforming data is through aggregation; for example, maximizing the ratio of good to bad output (Picazo-Tadeo et al. 2012). However, these transformations may significantly change the resulting efficiency estimates, and treating the output as an input is inconsistent with the physical transformation process and with standard production theory axioms (Cherchye et al. 2015, Färe and Grosskopf 2004).

For SFA, there exists similar or equivalent approaches to incorporating a detrimental output. Hyperbolic (Cuesta et al. 2009) and directional distance functions (Färe et al. 2005), modelled as translog and quadratic functions, respectively, can be used. The detrimental output can also be modelled as an input (Reinhard et al. 2000). Alternatively, the undesirable output can be aggregated with the beneficial output, for which there are many different methods in literature. For example, Bokusheva and Kumbhakar (2014) used a hedonic translog function to capture the relationship between good and bad outputs, and Fernandez et al. (2002) used Markov Chain Monte Carlo algorithm to endogenously capture the relationship. Cost and profit frontiers also allow for the incorporation of multiple outputs (Coelli et al. 2005). However, in these cases the detrimental output may require transformation such as using the additive or multiplicative inverse.

Each method has its advantages and drawbacks, and there appears to be no consensus on the best approach to model efficiency with an undesirable output (Cherchye et al. 2015). Song et al.'s (2012) extensive literature review concluded that there is a strong need for more research in methods and applications of modeling detrimental outputs.

3.5.4 Factors that affect efficiency

When estimating efficiency, it is also of great interest to researchers and policy makers to examine factors that potentially affect efficiency. Accounting for the exogenous factors that affect efficiency can take many forms. A two-stage approach is one of the first methods of seeing the impact of environmental variables on efficiency (Pitt and Lee 1981), and can be used for deterministic or stochastic frontiers. The first stage involves deriving efficiency estimates from a production frontier, and in the second stage, the efficiency estimates are regressed upon a vector of variables hypothesized to affect efficiency. However, concerns around this approach include potential correlation between technical inefficiency and the production function inputs leading to inconsistent estimates of efficiency (Kumbhakar et al. 1991), correlation between inputs and the variables in the second stage regression leading to biased frontier parameters, and statistical underdispersion of efficiency estimates causing downward biased efficiency model parameter estimates (Wang and Schmidt 2002).

With those issues present in two stage approaches, single stage estimation where the inefficiency model is jointly estimated with the production frontier has been proposed (e.g., Kumbhakar et al. 1991, Reifschneider and Stevenson 1991, Battese and Coelli 1995). Joint estimation of the inefficiency model, now the predominant approach used in empirical stochastic frontier studies, can be done through maximum likelihood or Bayesian approaches. For deterministic approaches such as DEA, the biased parameters in second stage regressions can be corrected for through the use of bootstrap procedures (Simar and Wilson 2007).

3.6 Literature Review

3.6.1 Dairy efficiency studies

Early studies on dairy technical efficiency used non-parametric approaches. For example, Weersink et al. (1990) estimated technical efficiency for Ontario dairy farmers following Färe et al.'s (1985) deterministic non-parametric programming approach. Inputs used in the production frontier were livestock expenses, feed, machinery, buildings, capital, labour, and other. The inefficiency model used was a second stage censored regression, where the variables included herd size, farmer experience, milk yield, butterfat, paid labour, feed purchased, debt to asset ratio, building per cow, horsepower of largest tractor, region dummies, business organization dummies, milking system dummies, and manure system dummies. Positive effects on efficiency were found from herd size, milk yield, and butterfat levels while proportion of purchased feed and overcapitalization had a negative effect.

In another early study, Cloutier and Rowley (1993) also used a non-parametric approach, DEA in their case, to study technical efficiency of Quebec dairy farms. The inputs they used were herd size, labour, land, feed, and other. Their study found DEA to be a readily applicable method of measuring efficiency, but the robustness of the efficiency estimates was questioned as the estimates were very sensitive to sample size.

SFA allows for the consideration of random shocks and measurement errors, both of which are common occurrences in agricultural studies. As such, studies utilizing stochastic measures of efficiency have become more common over time. For example, Mbaga et al. (2003) estimated technical efficiency for Quebec dairy farms and compared different functional forms (Cobb Douglas, translog, generalized Leontief) and distributional assumptions (half normal, truncated normal, and exponential), in addition to DEA measures. The inputs considered were: herd size, concentrate, forage, labour, capital, and genetic potential (proxied by weight of the cows). Statistical tests revealed that generalized Leontief forms dominated across all distributional assumptions. However, differences in the distributions of efficiency scores and output elasticities between all parametric models were not statistically different. Efficiencies were highly correlated between the alternative parametric forms, with low correlation between DEA and parametric specifications.

Another benefit of SFA is the ability to jointly estimate an inefficiency model. Van der Voort et al. (2014) used SFA to evaluate the impact of nematode infections on TE for dairy farms in Belgium. Inputs used in the frontier were: concentrate, forage, pasture, herd size, animal health costs, and labour. A joint inefficiency model with the level of exposure to nematodes as an explanatory variable was estimated. Two models were compared; neutral, where the environmental variable is independent of the inputs, and non-neutral, where the variable was interacted with the inputs. The study found an increase in nematode exposure led to a decrease in TE, with a larger effect on more efficient farms. In addition, the non-neutral SFA model revealed nematode infections caused inefficiency in the transformation of pasture, health and labour into milk but not the transformation of concentrate, roughage and dairy cows into milk.

Cabrera et al. (2010) studied technical efficiency and the effect of intensification[1] on Wisconsin dairy farmers using a stochastic production frontier with a Cobb Douglas

[1] Farming intensification is the process of increasing the use of inputs to increase agricultural production per land area (Eurostat 2018)

specification. The inputs in the production frontier were: herd size, cost of purchased feed, capital, crops, labour, and livestock expenses. A dummy variable to account for the effects of rBST on production was also included in the frontier model. An inefficiency model was jointly estimated with the production frontier using maximum likelihood following Caudill et al. (1995) where the variance of the inefficiency term is regressed on a vector of farm characteristics. These variables included: milking system dummies, housing dummies, milking frequency dummies, proportion of family labour, feed per cow, total mixed ration dummy, and pasture dummy. Conclusions from the study were a) rBST had a favorable impact on production, b) Wisconsin dairy production exhibited CRS, and c) efficiency increased with farming intensity, proportion of family labour, feeding total mixed ration, and milking frequency.

Jiang and Sharp (2015) compared TE between dairy farms in two regions in New Zealand using a SFA meta-frontier with a Cobb Douglas functional form. Inputs used were livestock, labour, capital, veterinary services, feed, fertilizer, and electricity. An inefficiency model following Battese and Coelli (1995) considering the variables farm size, parlour type, and intensity (cows per hectare) was jointly estimated with the frontier. They found TE increased with farm size, farming intensity, and the use of herringbone parlour technology, and that the two regions did not share the same production technology.

Skevas et al. (2017) studied the effect of farm characteristics on persistence of technical inefficiency of German dairy farms using a stochastic translog output distance function. Two outputs were considered, and both were beneficial outputs – milk, and livestock and other products. The model was estimated using Bayesian methods assuming an autoregressive process on TE. Frontier inputs were: buildings and machinery, labour, area, other, livestock units, feed, and regional dummy variables. Two forms of inefficiency models were estimated and compared – Battese and Coelli's (1992) and Emvalomatis et al.'s (2011) specifications, with farm size, specialization, and stocking density as the environmental variables. The study found the frontier and efficiency results were similar across the models with older farmers having higher technical inefficiency persistence.

Abdulai and Tietje (2007) also compared two alternative specifications to consider inefficiency effects for dairy farms in Germany. As unobserved firm heterogeneity can be confounded as inefficiency, the study corrected for potential heterogeneity bias through Greene's (2005) "true" random effects model using a translog functional form. The inputs used in their production frontier were feed expenses, livestock expenses, herd size, land, and labour. The random effects model was compared to Battese and Coelli's (1995) model, where the joint inefficiency model included the variables: assets, age, education, and off-farm work. The study found Battese and Coelli's (1995) model was more prone to heterogeneity bias than was the random effects model.

3.6.2 Dairy efficiency considering a detrimental output

As seen in the previous section, there are many possible models to estimate the efficiency of dairy farms. However, when considering a detrimental output, different approaches to efficiency measurement are taken. Earlier research in this area focused on nitrogen surpluses as the detrimental output. For example, Reinhard et al.'s (1999) study examined the technical efficiency of Dutch dairy farms with nitrogen surplus included as an input, using a stochastic translog production frontier. Other inputs used in the frontier were capital, labour, and variable inputs. Environmental efficiency (EE) was measured as the input orientated efficiency of a single input– nitrogen surplus. The study found intensive dairy farms were more efficient, both technically and environmentally.

Without including the detrimental output as an input, Fernandez et al. (2002) used SFA to study TE and EE for nitrogen surplus on Dutch dairy farms using Bayesian inference and Markov Chain Monte Carlo analysis. A Cobb Douglas functional form was used where TE was derived from a conventional production frontier, and EE from a frontier where the detrimental output is regressed on the good outputs. The inputs used were labour, capital, and an aggregate variable input. An inefficiency model was jointly estimated where the explanatory variables were: education, nitrogen fertilizer per hectare, and number of cows per unit of capital. The results revealed that EE and TE were positively correlated, education increased TE but not EE, fertilizer use increased TE and decreased EE, and increasing proportion of livestock capital decreased TE and EE.

Bokusheva and Kumbhakar (2014) took a similar approach to link two separate frontiers to study the technical efficiency of dairy farms when considering nitrogen surplus as a detrimental output. A two stage approach was taken where the first model aggregated the good and bad outputs using a translog hedonic output function while the second step was a stochastic translog input distance function. A second stage regression was estimated to assess the impact of the variables age, off farm employment, land ownership, investment to capital ratio, manure displacement, grazing land, input contracting, on-farm processing, and total subsidies on shadow prices. The study found increasing investments and subsidies led to higher shadow prices, suggesting that further pollution reduction may come at a high cost.

Mamardashvili et al. (2016) took an approach that did not require aggregation of the outputs. Their study implemented SFA to investigate the shadow price of nitrogen surplus for Swiss dairy farms using a hyperbolic distance function. Inputs considered were land, labour, capital, livestock, and materials. Following Kumbhakar and Lovell (2000), an inefficiency model was jointly estimated where the model and frontier variances were dependent on a vector of parameters to account for heteroskedasticity. The variables used in the inefficiency model were: part time farming, diversification of farming, organic farming, location, milk yield, and direct payments. The authors noted that the resulting average nitrogen abatement cost was high, at 28 Swiss francs per kg of nitrogen abated, suggesting it could be a reason for the difficulty in implementing nitrogen levies.

There have been a few studies that examined GHG emissions and dairy efficiency. Some use DEA; for example, Wetteman and Latacz-Lohmann (2017) used DEA to compare the effect of considering different objectives, minimizing costs versus minimizing GHGs, on technical efficiency for German dairy farms. Inputs considered were electricity, diesel, nitrogen, concentrates, and number of cows. The study found that shifting from cost efficient to GHG efficient production resulted in high abatement costs. In addition, farms that were more GHG efficient used a higher share of legumes and had a longer effective lifetime for their cows compared to cost effective farms.

Berre et al. (2013) used a directional distance function in a DEA context to compare shadow prices under society and farmer perspectives for dairy herds in Réunion, a French island east of Madagascar. Society's objective was defined as keeping good outputs constant while minimizing bad outputs while the farmer's objective was keeping bad outputs constant while maximizing good outputs. Two detrimental outputs were considered: nitrogen surplus and GHG emissions. The input variables were land, herd size, feed expenses, and labour. The study found a significantly higher shadow price for farmers than for society, and suggested that farmers can reduce pollution significantly if society compensated for the farmer's opportunity cost. Expanding on the study above, Berre et al. (2014) estimated an additional model to the two scenarios above that supported simultaneous contraction (expansion) of bad (good) outputs, and found that it was the most profitable way to reduce eco-inefficiency out of all the models tested.

Urdiales et al. (2016) used DEA to evaluate the eco-efficiency of dairy farms in Spain. They also examined the effect of socio-economic characteristics on efficiency using a bootstrapped truncated regression following Simar and Wilson (2007). Their study defined eco-efficiency as the ability to reduce all environmental pressures while maintaining the present level of production, where the bad outputs are GHGs and nutrient balances. The study found that farmers who were younger, planned to continue operating for at least five more years, participated in training schemes, had more positive attitudes towards pollution management, and had less positive attitudes towards regulation were more eco-efficient.

Shortall and Barnes (2013) studied the relationship between technical efficiency of dairy farmers and GHG emissions using a DEA methodology. Inputs considered were replacement animals, capital, labour, fertilizer, and feed. To account for the detrimental output, the indirect approach of DEA, where the GHG variable is transformed, was used. Three measures of TE were compared: TE without considering GHGs, TE with GHGs as an input, and TE with two beneficial outputs (milk and the inverse of GHGs). For the second stage inefficiency model, a Tobit model was used to see the effects of herd size, milk yield per cow, farmer qualifications, and years of experience. The study found that the three forms of TE were highly correlated and that increasing herd size and milk yield per cow led to higher efficiency scores.

For SFA, the literature examining GHG emissions for dairy farms is limited. One such study is by Dayananda (2016), who examined technical and environmental efficiencies for Ontario dairy farms using a stochastic input distance function, where EE was calculated following Reinhard et al. (1999). The beneficial outputs considered were milk, livestock, and crops, while the detrimental output was GHG emissions. Inputs used in the frontier were feed, capital, labour, and other. Inefficiency models, estimated using second stage regressions, included age, education, and herd size as explanatory variables. The study found that TE and EE were highly positively correlated and that EE increased with herd size. However, their study used an input distance function approach, which considers technical efficiency as the ability to minimize inputs, keeping both desirable and undesirable outputs constant. While keeping milk output constant can be a representative objective, keeping GHG emissions constant may not be a realistic practice.

Njuki and Bravo-Ureta (2015) allowed for more flexibility in the efficiency objectives (i.e., GHGs not held constant) by using quadratic directional distance functions. An SFA approach was taken to study the effect of GHG regulations on American dairy farmers. Three outputs were considered; milk, an aggregation of crop and livestock outputs, and GHG emissions. The inputs were herd size, labour, machinery, concentrate, and forage. Time and temperature variables were also included in the frontier to account for technical change and environmental effects, respectively. Diverse shadow prices, interpreted as the marginal abatement cost, were found across different counties, suggesting that flexible assistance programs rather than inflexible command and control regulations should be considered. However, their study did not incorporate factors that can affect efficiency, compare the efficiencies with and without considering GHGs, or evaluate production elasticities.

Overall, common inputs for the production frontier used by dairy farm efficiency studies include: feed, herd size, land, capital, and other variable costs. For factors that affect efficiency, many studies consider age, education, farming intensity, farm size, and degree of specialization. For modelling inefficiency, there are many types of models present in the literature, with no apparent dominant methodology. In addition, it can be concluded from the review of previous studies that directional and hyperbolic distance functions are a popular way to consider a detrimental output if researchers do not wish to aggregate the outputs, use DEA, or treat the detrimental output as an input. There are also gaps in current literature regarding dairy farm GHGs and technical efficiency, and addressing some of them will be one of the contributions of this study; for example, evaluating the efficiencies from SFA and DEA, the effect of farm and producer characteristics in an SFA context, and the production elasticities considering GHG emissions.

3.7 Chapter Summary

This chapter begins with a review of the theory behind production functions. As conventional production frontiers are inadequate for modeling detrimental outputs in a multi-output production context, an overview to alternative measures is then provided. In particular, directional and hyperbolic distance functions are covered. Concepts and empirical considerations for efficiency analysis are also provided. Relevant studies are then reviewed, revealing gaps in dairy efficiency literature that consider GHG emissions. Gaps addressed by this study include: measuring efficiency from both SFA and DEA contexts, factors that affect technical and environmental efficiency, and the production elasticities considering GHG emissions.

Chapter 4. Stochastic Frontier Analysis

As discussed in Chapter One, the objectives of this study are to estimate multi-output production frontiers that incorporate desirable and undesirable outputs for Alberta dairy production, study the relationship between efficiencies calculated with and without considering environmental impacts, identify management practices and farm characteristics correlated with "sustainable" farms, and estimate the shadow price of GHG emissions for Alberta dairy farms. For a well-rounded consideration of these objectives, two separate analyses are performed. The first is an econometric analysis of the large dataset using stochastic frontier analysis (SFA), which is discussed in this chapter. The second uses data envelopment analysis (DEA) for a smaller but more detailed subset of the data. The DEA analysis is presented in Chapter Five.

The objectives of the analysis undertaken in this chapter are to estimate parametric stochastic production frontiers with and without considering GHG emissions, and compare the resulting efficiencies, elasticities, shadow prices, and inefficiency model parameters to assess the relationship between GHG emissions and economic indicators of farm performance. This chapter begins with a discussion of the empirical model and econometric considerations. Next, an overview of the data and how the variables are derived is provided. The SFA results are then presented, including findings such as the comparison of efficiency estimates, factors that affect efficiency, production elasticities, and shadow prices. The chapter concludes with a summary of the sensitivity analysis and the robustness of the results.

4.1 Empirical Model

Dairy production is characterized by variability in milk production due to a combination of management and environmental factors. Thus, it is appropriate to model technical efficiency by estimating a stochastic frontier. The previous chapter provided a discussion of the advantages of SFA, and many are directly applicable to this study. For example, one of the study datasets is comprised of unbalanced panel data, and unlike DEA, SFA can directly consider the panel nature of the data. The size of this dataset is also adequate for the computational requirements of SFA. In addition, this study utilizes farm production data, and SFA accounts for the stochastic nature of agricultural operations (e.g., shocks from weather and disease) by differentiating between random noise and producer inefficiency. Other advantages of SFA include the ability to use statistical analysis (e.g., tests of significance), less sensitivity to outliers and measurement errors, and the simultaneous estimation of an inefficiency model without the need for bootstrapping. Overall, the attributes of SFA align closely with the objectives for this study.

For SFA, a functional form must be assumed. However, a typical production frontier is insufficient for this study due to the need to consider multiple outputs where one of the outputs is undesirable. As seen in the previous chapter, there are many ways to include a detrimental output for SFA; for example, modeling the output as an input, aggregating the desirable and undesirable outputs, and using hyperbolic or directional distance functions. As different aggregation methods can lead to highly variable results, and treating an output as an input is inconsistent with conventional production theory axioms and the physical transformation process, the distance function approach is chosen for this study.

Between the two types of distance functions that can accommodate a detrimental output, hyperbolic and directional, the hyperbolic distance function is used for this study. One reason for this choice is that results from directional distance functions are highly dependent on the direction vectors chosen, and clear guidelines for choosing directional vectors have not yet been established (Cherchye et al. 2015). In addition, hyperbolic distance functions may more closely resemble standard Farrell-type efficiency as multiplicative radial scaling is used to derive efficiency.

There are two types of hyperbolic distance functions: regular, which involves the equiproportional expansion/contraction of the good/bad output vectors, and enhanced, which considers the equiproportional expansion of the good output vector and contraction of the bad output and input vectors (Cuesta et al. 2009). Because the enhanced model also considers the proportional contraction of inputs, the results from the enhanced hyperbolic distance function are comprehensive economic performance measures that consider the ability of the producers to simultaneously maximize beneficial outputs, minimize detrimental outputs, and minimize inputs (Cuesta et al. 2009). As such, the enhanced specification is used for this study.

4.1.1 Enhanced hyperbolic distance function

As discussed in Chapter Three, the enhanced hyperbolic distance function can be represented as follows:

$$D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) = \inf\{\theta \geq 0 \colon \left(\boldsymbol{x}\theta, \frac{\boldsymbol{y}}{\theta}, \boldsymbol{b}\theta\right)\} \tag{4.1}$$

where the distance (D_H), which can be also be interpreted as producer efficiency, is represented by the scalar θ; as such, it reflects the producer's ability to expand the desirable output vector ($\boldsymbol{y}$), contract the undesirable output vector ($\boldsymbol{b}$), and contract the input vector ($\boldsymbol{x}$). Empirically, with the almost homogeneity property (Equation 4.2), hyperbolic distance functions can be represented using a translog functional form.

$$D_H(\mu^{-1}x, \mu y, \mu^{-1}b) = \mu D_H(x, y, b), \mu > 0 \tag{4.2}$$

Specifically, Equation 4.3 represents the translog hyperbolic model considering N producers, T time periods, K inputs, M beneficial outputs, and one bad output (b):

$$\begin{aligned} lnD_{Hi,t} = {} & \alpha_0 + \textstyle\sum_{k=1}^{K} \alpha_k lnx_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl}\, lnx_{kit} lnx_{lit} + \sum_{m=1}^{M} \beta_m lny_{mit} + \\ & \tfrac{1}{2}\textstyle\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_m\, lny_{mit} lny_{nit} + \delta lnb_{it} + \sum_{k=1}^{K}\sum_{m=1}^{M} \gamma_{km}\, lnx_{kit} lny_{mit} + \\ & \textstyle\sum_{m=1}^{M} \theta_{mb} lny_{mit} lnb_{it} + \sum_{k=1}^{K} \theta_{kb} lnx_{kit}\; lnb_{it}\,,\; (i = 1,2, \dots, N\,; t = 1,2, \dots, T) \end{aligned} \tag{4.3}$$

Returning to the almost homogeneity condition, μ is chosen to be the inverse of one of the good outputs (y_M):

$$D_H(xy_M, \frac{y_m}{y_M}, by_M) = \frac{D_H(x,y,b)}{y_M} \tag{4.4}$$

The transformed function becomes:

$$\begin{aligned} ln(\frac{D_{Hit}}{y_M}) = {} & \\ & \alpha_0 + \textstyle\sum_{k=1}^{K} \alpha_k lnx^*_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl}\, lnx^*_{kit} lnx^*_{lit} + \sum_{m=1}^{M-1} \beta_m lny^*_{mit} + \\ & \tfrac{1}{2}\textstyle\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn}\, lny^*_{mit} lny^*_{nit} + \delta lnb^*_{it} + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \gamma_{km}\, lnx^*_{kit} lny^*_{mit} + \\ & \textstyle\sum_{m=1}^{M-1} \theta_{mb} lny^*_{mit} lnb^*_{it} + \sum_{k=1}^{K} \theta_{kb} lnx^*_{kit}\; lnb^*_{it}\,,\; (i = 1,2, \dots, N\,; t = 1,2, \dots, T) \end{aligned} \tag{4.5}$$

where: $x^*_{kit} = x_{kit}\, y_M,\; b^*_{it} = b_{it}\, y_M,\; y^*_{mit} = \frac{y_{mit}}{y_{Mit}}$

Moving lnD_H to the right hand side of the equality, it can be interpreted as the inefficiency component of the error term (i.e., u_{it}), and the resulting function (Equation 4.6) can be estimated econometrically.

$$-lny_{Mit} = Translog(x^*_{kit}, y^*_{mit}, b^*_{it}) + (v_{it} - u_{it}) \tag{4.6}$$

To obtain the technical efficiency estimates, the following equation is calculated:

$$TE_{it} = E\left[e^{(-u_{it})} \middle| (v_{it} - u_{it})\right]. \tag{4.7}$$

The production frontier and efficiency results for the hyperbolic distance function that does not consider GHGs are calculated in the same manner, with the exception being terms with b_{it} are not included.

4.1.2 Distributional assumptions

To estimate stochastic frontier models, assumptions regarding the distribution of the error terms are necessary to decompose the composite error into stochastic noise, v_{it}, and inefficiency, u_{it}. For the stochastic noise term, the most common distribution used in literature is *i.i.d* $N(0, \sigma_v^2)$ (Coelli et al. 2005), which this study follows for the distribution of v_{it}.

Since the inefficiency term is restricted to be non-negative, the distribution chosen for u_{it} should reflect this property. Potential choices include the half normal, truncated normal, exponential, and gamma distributions. The half normal distribution (Aigner et al. 1977) can be represented u_{it}~ *i.i.d* $N^+(0, \sigma_u^2)$. The truncated normal distribution (Jondrow et al. 1982) is similar to the half normal, differing in that the mean can deviate from zero: u_{it}~ *i.i.d* $N^+(\bar{u}, \sigma_u^2)$. The exponential (Meeusen and van der Broeck 1977) and gamma (Greene 1990) distributions can be represented u_{it}~ *i.i.d*

$G(\rho, 0)$ and u_{it}~ *i.i.d* $G(\rho, n)$, respectively, where ρ is the mean, and n is the degrees of freedom.

There are advantages and disadvantages associated with each alternative distributional assumption. For example, half normal and exponential distributions have means at zero, implying that a large proportion of the sample have inefficiencies close to zero. Truncated normal and gamma distributions allow more flexibility in the shape of the distribution; however, they are more computationally intensive. Mbaga et al. (2003) studied the effect of varying the above distributions on the efficiency on dairy farms in Quebec, and found that different distributions lead to statistically different efficiency estimates, but with minimal impact on the rank correlations. As such, the distribution of the inefficiency term is a significant but not critical decision when estimating stochastic frontiers.

For this study, a truncated normal distribution is assumed for the inefficiency term u_{it}, allowing for flexibility and for integration of an inefficiency model. Truncated normal distributions are used in many dairy efficiency studies; for example, Abdulai and Tietje (2007), Jiang and Sharp (2015), Reinhard et al. (1999), and van der Voort et al. (2014).

4.1.3 Inefficiency model

Factors that affect efficiency are of great interest to researchers and policy makers. One advantage of SFA is that it allows for simultaneous estimation of an inefficiency model to evaluate the effects of farm and producer characteristics on efficiency. There are many ways to model inefficiency effects in a single stage estimation (e.g., Kumbhakar et al. 1991, Reifschneider and Stevenson 1991, Battese and Coelli 1995). For this study, the Battese and Coelli (1995) specification is chosen as it can accommodate panel data. Assuming a truncated normal distribution for the inefficiency term u_{it}, it can be expressed:

$$u_{it} \sim i.i.d\ N^{+}(z_{it}\varphi, \sigma_u^2) \tag{4.8}$$

where z_{it} is a vector of variables associated with technical efficiency, and φ is a corresponding vector of coefficients to be estimated.

Maximum likelihood methods are used to estimate the stochastic frontiers and joint inefficiency models. Specifically, the package 'frontier' developed by Coelli and Henningsen (2017) for R is used for this analysis.

4.2 Data

The data used for this study are from the Alberta Dairy Cost Study, and include information on farm expenses, milk output, livestock numbers, feed components, and farm specific characteristics such as years farming and farm location. The Alberta Dairy Cost Study is a survey administered by the Economics Section at Alberta Agriculture and Forestry in cooperation with Alberta Milk (AAF 2017c). The survey tracks the costs and returns of dairy production in Alberta, and provides insight into whether milk pricing reflects the cost of production (AAF 2017c). Between 40 and 60 producers are surveyed each year, where participants complete monthly surveys on herd inventory, capital purchases, milk sales and usage, feed use, and feed costs. Sample monthly survey forms can be found in Appendix H.

The study sample consists of unbalanced panel data from the Dairy Cost Study for the years 1996 to 2016, with observations from the year 2008 removed. The observations for 2008 are dropped due to concerns about the accuracy of recorded/reported production levels. In 2008, the Canadian dairy industry shifted to a total production quota system from a two-tiered quota system, which changed the data coding system. The individual with Alberta Agriculture and Forestry most familiar with the Dairy Cost Study data expressed concern that, due to the adjustment required for the new costing system, production levels in 2008 may not be accurate.

Attempts were made to avoid the need to discard 2008 observations. This included representing production levels using revenue as a proxy, or adding a dummy variable for the year 2008. However, these models did not converge as well as the model with 2008 observations removed (see Appendix I). Observations where livestock sales are zero, of which there are ten in total, are also removed to allow for estimation of a translog functional form. In addition, one outlier is omitted due to a very low total milk production level that did not match its reported milk revenue. After considering the data omissions, a total of 1075 observations from 212 producers are used for SFA.

4.3 Variables

The variables chosen for use in this study are based on literature review, data availability, and econometric feasibility. The detrimental output variable is GHG emissions, where, as seen in previous chapters, studies in this area are limited and there is a need for more understanding to better align producer incentives with GHG reduction. The two beneficial outputs are milk and livestock as these comprise the majority of revenue for dairy farms in Canada (CDC 2017a). For inputs, forage, concentrate, labour, capital, and "other" are used. Feed inputs are separated into forage and concentrate due to their differing effects on GHG emissions and productivity (see Section 2.2.2). Herd size is also a common input for dairy production frontiers; however, models including herd size for this study displayed low statistical significances for the parameters (see Appendix G). As a result, livestock capital is aggregated with other forms of capital into one inclusive capital variable for this study.

4.3.1 Outputs

4.3.1.1 Greenhouse gas emissions

GHG emissions from the dairy enterprise, measured in CO_2 equivalents, are used as the detrimental output for this study. Emissions arise from a number of sources on dairy farms; for example, enteric fermentation, manure management, cropping practices, and energy use. Rather than focusing on specific production areas or type of GHG, a holistic approach to measuring GHG emissions is used for this study because emission reductions in one area of farm management can lead to increases in another. As such, this study considers emissions throughout the entire production chain for the dairy enterprise, beginning with the production of inputs such as fertilizer and herbicides, and finishing at the farm gate. To capture these whole-farm emissions, algorithms from Holos, an AAFC emissions simulation model (Little et al. 2013), are used to calculate GHG emissions from dairy production data.

For this study, instead of using the Holos software, the algorithms are programmed into Microsoft Excel. This allows for customization to Alberta specific assumptions, as well as for greater time efficiency as the Holos software requires each observation to inputted individually. To ensure the calculations from the Excel spreadsheet match those from Holos, GHG emissions calculated from both programs are compared, using 20 observations that cover a variety of time periods, farm sizes, and regions (Appendix C). Overall, differences are minimal, with the maximum difference in total emissions being 1.37%. The subsections below provide explanation of how Holos is used to calculate emissions for individual dairy farm observations and what data and assumptions are used.

4.3.1.1.1 Holos

Holos is a software program developed by AAFC researchers as an exploratory tool to test possible ways to reduce GHGs for individual farms (Little et al. 2008). Users may select scenarios and farm management practices– for example, changing feed, tillage, or crops planted, to see the effect on GHG emissions. For a more in-depth look at farm GHG emissions, users may also adjust each individual parameter manually to create their own scenario. For this study, algorithms from the software Holos are used to estimate the GHG emissions from dairy farms. Holos algorithms are based on Intergovernmental Panel on Climate Change (IPCC) guidelines (IPCC 2006), and are adapted for specific Canadian regions based on Canadian research (e.g., CDIC 2007, Dyer and Desjardins 2007, Rochette et al. 2008, Vergé et al. 2007).

Holos considers whole farm GHG emissions, including emissions from the production of inputs (e.g., fertilizers and herbicides) and all farm operations up until the farm gate. Sources of emissions considered by Holos include enteric fermentation, manure, cropping, and energy use. In addition, Holos also considers carbon storage and loss from land use changes and lineal tree plantings. Livestock included in the

Holos program are beef, dairy, swine, poultry, sheep, and other (e.g., bison, deer, horses, goats). Crops included are annual crops, perennial forages, fallow area, grassland/pasture, and tree plantings.

For this study, the GHG emissions considered are: enteric methane, manure methane and nitrous oxide emissions, soil nitrous oxide emissions from cropping, and carbon dioxide emissions from energy use for cropping and dairy operations. Assuming negligible carbon flux, carbon flows from land use changes are not included in this study to allow focus on GHGs directly from the dairy operation. Appendix A provides the Holos algorithms used in this study and Appendix B includes the default parameter values used in the Holos algorithms.

4.3.1.1.2 Enteric methane emissions

Enteric methane is the methane produced from fermentation of complex carbohydrates in the rumen of cattle, and it comprises a major portion of dairy GHG emissions (Boadi et al. 2004). Enteric methane production depends on several factors such as ration ingredients, energy requirements of the animals, amount consumed by the animal, presence of fat or other feed additives, animal body weight, and animal type (Boadi et al. 2004). For Holos, enteric methane emissions are calculated based on the methane conversion factor of feed, level of fat in the diet, and gross energy intake (Equation A.1).

The methane conversion factor is the proportion of gross energy intake that is transformed into methane; for example, it will be higher for feeds with a greater proportion of roughage relative to concentrate. For the methane conversion factor, Holos defaults for each cattle group and diet type are used (Table B.2). Feeding lipids can reduce enteric methane emissions, and the percentage of fat in the diet is used to calculate enteric methane emissions. As the Dairy Cost Study does not include lipids in their collection of feed components data, this study assumes lactating animals are the only animal group to have fat in their diet, at a level of 2%, as suggested by Eastridge (2014) and Hutjens (1998).

Gross energy (GE) of a feed is measured by the heat produced when feed is burned in a calorimeter, and varies by the type of feed. GE intake is dependent on the digestibility of the feed and the energy needs of the animal. Assuming that feed intake is equal to energy requirements, Holos calculates gross energy (GE) intake from the total digestible nutrients (TDN) content of the ration and net energy requirements of the animals (Equation A.2).

TDN is the sum of the digestible fiber, protein, lipid, and carbohydrate components of a feed. Holos defines three categories of TDN levels in diets: low, medium, and high (Table B.2). The Dairy Cost Study provides information on total feed usage by the dairy enterprise, without separating feed consumption by each animal category. As a result, this study assumes that TDN content is directly related to the amount of concentrate[2] included in the ration, and the Holos categories are assigned to observations that fall within certain thresholds of concentrate fed per milking head. To find the thresholds, total concentrate used by the farm is divided by the number of milking cows, as milking cows typically consume the largest proportion of concentrate. A range of 0.19-7.33 tonnes/cow/year is found, and the parameters chosen for the

[2] For this study, concentrate consists of the higher energy feeds such as grains, supplements, minerals, molasses, and brewer's grain.

thresholds for lactating cows are: less than 2.62 tonnes/cow/year for low TDN diets, between 2.62 and 4.45 tonnes/cow/year for medium TDN diets, and greater than 4.45 tonnes/cow/year for high TDN diets. These parameters are determined by looking for natural breaks in the dataset while aligning with literature estimates; for example, Broderick (2003) defined 2.19 tonnes/cow/year of concentrate as low, 3.25 as medium, and 4.75 as high.

Holos only has low and medium TDN options for heifers and bulls. As a result, it is assumed that farms that feed high or medium energy to lactating cows feed medium energy diets to heifers/bulls, while farms that feed low energy diets to lactating cows will also feed low energy to heifers/bulls. Following Holos, calves are assumed to be milk-fed. For dry cows, Holos provides two TDN options– one for close-up (i.e., close to parturition) and one for far-off dry cows (Table B.2). As the Dairy Cost Study does not differentiate between close-up and far-off dry cows, the average of the defaults for those two options is used, under the assumption farms have the same proportions of close-up and far-off dry cows.

Net energy (NE) is the energy available after digestive and metabolic losses for the requirements of maintenance, activity, lactation, pregnancy, and gain. For Holos, these requirements are calculated based on body weight, days at each production stage, activity level, milk production, butterfat level, and average daily gain (ADG). Of these factors, parameters that can be directly obtained from the Dairy Cost Study are milk production and butterfat levels.

For animal weights, the Holos defaults are used for the weight of lactating cows, dry cows, bulls, and initial weight of calves (Table B.1). For calves and heifers, this study deviates from Holos because Holos assumes that calves are raised for veal, which is not a common practice in Alberta (Corbett 2016). The calf and heifer assumptions for this study are represented in Table 4.1. For calves, it is assumed that surplus calves are kept for an average of three weeks before being sold, as it is common in Alberta for calves to be immediately sold or kept for at least six weeks (Corbett 2016). For simplicity, it is assumed calves move to the heifer stage at three weeks of age. As such, the starting weight of young heifers, following the ADG suggested by Chester-Jones and DiConstanzo (2012), is 51.4 kg. This study also follows PennState Extension (2017) guidelines; Holstein heifers are typically bred at 16 months of age at a weight of 363.6 kg. For the time spent at the bred heifer stage, this study uses the typical gestation period for Holstein cows of 279 days (BCSPCA 2017). Additional ADG assumptions used for this study include: male and female animals have similar ADG, ADG varies with low and medium diets, ADG is constant over the 1996-2016 sample period, and only heifers and calves are gaining weight (i.e., they have positive NE of gain requirements).

For net energy requirement for activity, the main determinant is the type of housing. Total pasture acres is included in the Dairy Cost Study; however, the housing type and the animal categories that are housed on pasture are not specified. As dairy animals in Alberta are typically not on pasture (Corbett 2016), this study assumes all animal groups, with the exception of bred heifers, have limited activity (i.e., housed in a barn or drylot). For farms where the observed pasture acres per cow exceeds 0.25, the

Table 4.1 Weights and durations for each production stage for calves and heifers

Animal group	Diet type	Days grown	Initial weight (kg)	Final weight (kg)
Bred heifer	Low	279	363.6	552.5
	Medium	279	363.6	585
Young heifer	Low	460	54.4	363.6
	Medium	369	51.4	363.6
Calf	Milk	21	40	51.4

bred heifers are assumed to be on pasture grazing less than three kilometers per day for the months of June to October.[3]

For the net energy of pregnancy, this study uses a different assumption from Holos. It takes approximately two months after parturition before dairy cows are bred again, and there is a 43% pregnancy rate in Alberta (Ambrose and Colazo 2007), leading to an estimated 35.8% of dairy cows that are pregnant, and this value is used instead of the Holos assumption that all dairy cows are pregnant.

4.3.1.1.3 Methane and nitrous oxide emissions from manure

Manure from dairy operations can generate both methane and nitrous oxide emissions. The majority of manure methane originates from anaerobic decomposition of manure (Hristov et al. 2013). Direct nitrous oxide emissions are from the nitrification and de-nitrification of nitrogen in manure whereas indirect nitrous oxide emissions are from volatilization of nitrogen in the form of ammonia or nitrogen oxides (Hristov et al. 2013).

Manure methane emissions vary by storage system and manure contents. Holos calculates manure methane from the volatile solids production by the animals and the manure storage system (Equations A.10, A.12). Volatile solids are the organic matter in

[3] This housing trend is reflected in responses to the study questionnaire sent to producers in 2016, which is discussed further in Chapter 5.

manure; that is, the content that is susceptible to further decay. Volatile solid production is dependent on GE and TDN (Equation A.11), and the derivation of these parameters is discussed above. With respect to manure storage, based on consultation with an Alberta dairy manure management expert (Wallace 2016), this study assumes solid manure storage for calves, bulls, and heifers, while liquid storage with natural crust cover is assumed for lactating cows. Manure storage for dry cows depends on herd size; dairy herds over 120 head are assumed to have liquid storage while smaller herds use solid storage for dry cows. In addition, this study assumes liquid manure is spread twice a year during the months of April and October, following typical manure spreading practices in Alberta (Wallace and Landiak 2013).

For manure nitrous oxide emissions, direct and indirect N_2O emissions depend on the storage system and the nitrogen excretion rate (Equations A.19 and A.25). The nitrogen excretion rate is calculated based on crude protein consumption, milk production, body weight, and ADG. For this study, crude protein percentage of the diet is assumed to follow the Holos defaults, and varies by diet and animal group (Table B.2).

4.3.1.1.4 Soil nitrous oxide emissions

Similar to manure, direct soil nitrous oxide emissions originate from nitrification and de-nitrification of nitrogen from sources such as fertilizer, land applied manure, and crop residue. Indirect soil nitrous oxide emissions are generated from volatilization and leaching of nitrogen. Factors that affect soil nitrous oxide emissions are the soil type and texture, land topography, precipitation, evapotranpiration rate, tillage practices, area of crop land, and amount of nitrogen applied from fertilizer, manure, and crop residue.

To capture many of the factors that affect soil nitrous oxide emissions, an ecodistrict is identified for each observation. An ecodistrict is an area assumed to share a common soil texture, topography, soil type, precipitation, and evapotranspiration value. Through cross-referencing the ecodistrict map (Appendix D) with the observed county, an ecodistrict is assigned to each county represented in the Dairy Cost Study (Appendix E).

Tillage practices are another factor to consider when calculating soil nitrous oxide emissions. The Dairy Cost Study does not include data on tillage practices. As such, the Holos categories of conventional tillage, reduced tillage, and no-till are assigned to observations based on Statistics Canada data. A linear time trend is interpolated from Agricultural Census data (Statistics Canada 2008, 2014a) for the years included in the study sample, and the dominant annual tillage practice (i.e., used for over 50% of acres) is applied to all observations that year, as the regional differences in tillage practices do not appear to be significant (Statistics Canada 2012c). The resulting assumptions are: intensive tillage for 1996–1998, reduced tillage for 1999–2006, and no till from 2007 onwards.

Another determinant of soil N_2O emissions is the area of crop land, and this study considers the area of annual crops, perennial forages, and fallow. The cropping area includes emissions from all the feed used for the dairy operation[4], whether it is

[4] Processed feed (i.e., beet pulp, molasses, protein supplement, calf feed, milk replacer, salt, mineral and vitamins, and brew grain) are not included in the total cropping area due to difficulty identifying accurate cropping parameters. Instead, emission factors are used for processed feed.

grown directly on the farm or produced elsewhere[5]. The Dairy Cost Study provides information on the total amount of feed used by the dairy enterprise, but not individual cropping areas for each crop. As a result, an estimate of the total cropping area is calculated using crop yields, field and harvest losses, and fallowing practices. For this study, field and harvest losses are assumed to be: 10% for straw, 15% for forages (Manitoba Agriculture n.d.), and 3% for grains (Rocquigny 2015).

As the Dairy Cost Study does not collect information on crop yields, yields for the crops included in the Dairy Cost Study (i.e., oats, barley, wheat, mixed grain, hay, alfalfa hay, greenfeed, and silage) are identified from other sources. For oats, barley, wheat, mixed grain, hay, and alfalfa hay, yields are obtained from Agriculture Financial Services Corporation (AFSC). As the AFSC data has large fluctuations from year to year, this study uses the average of the yields across the years present in the AFSC data that are relevant to this study (1996-2013) (Table 4.2).

In addition to hay, silage and greenfeed are other forage sources for dairy operations in Alberta. Silage is a fermented forage that comprises a major proportion of dairy feed, and it is commonly produced from barley, corn, or alfalfa (Alberta Milk 2017b). In Alberta, greenfeed is a cereal crop hay that is typically grown from oats or barley (AAF 2015c, AAF 2016b). For silage and green feed yield, due to data limitations, a constant yield over region and time is assumed (Table 4.3). For this study, two categories of silage are assumed to be fed to cattle: corn silage and all other types of silage. All other types of silage is predominantly barley silage, but can also include alfalfa, oats, and wheat (AAF 2016b).

[5] This study assumes negligible transportation emissions.

Table 4.2 Crop yields (kg/ha)

Ecodistrict	Barley Grain	Oat	Wheat[a]	Mixed Grain[b]	Alfalfa	Hay
600	2931.59	3247.43	2648.49	3089.51	3699.21	5648.23
623	3076.57	2745.33	2690.48	2910.95	10368.17	9057.25
681	3758.96	3510.86	3602.65	3634.91	10479.72	10479.72
683	3589.02	3307.42	3490.60	3448.22	12669.65	11370.99
684	3283.30	3185.74	3320.29	3234.52	9535.21	8670.30
687	3323.57	3034.32	2752.66	3178.94	6737.50	6744.03
692	3076.57	2745.33	2690.48	2910.95	10368.17	9057.25
703	3615.40	3338.39	3527.34	3476.89	12207.91	10482.24
708	3615.40	3338.39	3527.34	3476.89	12527.87	10667.56
727	3589.02	3307.42	3490.60	3448.22	12669.65	11370.99
728	3219.47	2950.56	2738.17	3085.02	9471.82	7568.30
730	3220.12	2834.27	2779.80	3027.19	4970.24	6539.91
731	3176.08	2518.63	2741.61	2847.36	8334.83	8658.25
737	3615.40	3338.39	3527.34	3476.89	12207.91	10482.24
738	3224.53	2437.90	2677.22	2831.22	4785.19	6955.18
740	3176.08	2518.63	2741.61	2847.36	8334.83	8658.25
744	3615.40	3338.39	3527.34	3476.89	12207.91	10482.24
746	3860.48	3223.37	3809.52	3541.92	15774.41	10592.94
750	3431.77	2486.12	3168.03	2958.94	11705.68	6737.47
769	1968.26	1808.79	1869.30	1888.53	4785.19	8530.23
781	3848.00	3051.74	3336.88	3449.87	8237.15	9200.34
788	3129.92	2486.12	3168.03	2958.94	11705.68	9200.34
790	3129.92	2486.12	3168.03	2958.94	11705.68	9200.34
793	3889.16	2272.59	3304.15	3080.87	12221.81	10128.56
797	3763.35	2125.18	3348.35	2944.26	12221.81	7064.01
798	3431.77	2486.12	3168.03	2958.94	11705.68	9200.34

[a] This study assumes that all wheat grown is hard red spring (Statistics Canada 2016)
[b] Mixed grain and greenfeed are calculated assuming a mix of 50% barley and 50% oats following common practice in Alberta (AAF 2016b)

Table 4.3 Yields of silage and greenfeed

Crop	Yield (kg/ha)
Corn silage	38301
Other silage	13813
Greenfeed	6153

Source: Kosinski (2012)

Calculating the total area of silage grown requires information on the proportion of corn silage relative to other silage grown. The Dairy Cost Study reports quantities of silage fed but not by type of silage, so the proportion of corn silage grown is estimated from other sources. Data on corn silage production are available by agricultural region (Statistics Canada 2014b), where agricultural regions are the regional divisions used for the Canadian Agricultural Census (see agricultural region map in Appendix F). However, data for total silage production by agricultural region in Alberta are not available. As silage is a high moisture feed that can be infeasible to transport, the assumption of limited transportation of silage is used. As such, silage production can be approximated by head of cattle. Using total cattle per agricultural region (Statistics Canada 2014c) and the silage yields in Table 4.3, the proportions of corn silage per agricultural region in Alberta for 2011 is estimated (Table 4.4).

However, these proportions are likely biased downwards as cattle populations in Alberta are predominantly from beef herds (Statistics Canada 2017a), and beef feedlots typically feed a higher proportion of grain and lower proportion of silage in their diet (Li et al. 2014). With this in consideration, as well as taking into account recommendations from Alberta dairy nutritionists (McAllister 2016, Robinson 2016), the corn silage proportions are adjusted for this study (Table 4.4). Alberta corn silage production also displays a time trend (Statistics Canada 2012b). If assumed to be linear, corn silage production in Alberta increases at 5.37% per year, and this trend is reflected in the corn silage percentages used for this study (Table 4.5).

Fallow area, the area of cropland that is left out of production as part of crop rotation practices, also produces soil emissions. As fallowing practices are not collected

Table 4.4 Percentage of corn silage out of total silage fed for 2011

Agricultural Region	Corn silage proportion based on cattle populations	Adjusted corn silage proportion for this study
1	46%	50%
2	60%	65%
3	5%	35%
4A	15%	35%
4B	45%	35%
5	30%	35%
6	25%	30%
7	12%	15%

Table 4.5 Percentage of corn silage through time and agricultural region

	Agricultural Region				
Time	1	2	3,4,5	6	7
1996	9.72	12.64	6.81	5.83	3.89
1997	12.41	16.13	8.69	7.45	4.96
1998	15.10	19.62	10.57	9.06	6.04
1999	17.78	23.11	12.45	10.67	7.11
2000	20.47	26.60	14.33	12.28	8.19
2001	23.15	30.10	16.21	13.89	9.26
2002	25.84	33.59	18.08	15.50	10.33
2003	28.52	37.08	19.96	17.11	11.41
2004	31.21	40.57	21.84	18.72	12.48
2005	33.89	44.06	23.72	20.33	13.56
2006	36.58	47.55	25.60	21.95	14.63
2007	39.26	51.04	27.48	23.56	15.70
2008	41.95	54.53	29.36	25.17	16.78
2009	44.63	58.02	31.24	26.78	17.85
2010	47.32	61.51	33.12	28.39	18.93
2011	50.00	65.00	35.00	30.00	20.00
2012	52.69	68.49	36.88	31.61	21.07
2013	55.37	71.98	38.76	33.22	22.15
2014	58.06	75.47	40.64	34.83	23.22
2015	60.74	78.96	42.52	36.44	24.30
2016	63.43	82.45	44.40	38.06	25.37

by the Dairy Cost Study, this study uses an estimated rate of fallow per cropland, which is then multiplied by total cropping area to find the area of fallow. Using Agricultural Census data from Statistics Canada (2008, 2012a), total acres of fallow is divided by total cropping acres. Assuming a linear time trend, fallow in Northern Alberta[6] decreases at a rate of 0.31% per year, and by 1.7% per year in the South. These trends are used to interpolate the rates of fallow for years not covered by the Census (Table 4.6). Fallowing practices can be separated by methods of weed control– herbicide or tillage. From the trends suggested by Statistics Canada (2008, 2017e), this study assumes North Alberta does not use herbicide until 2011 onwards while South Alberta does not use herbicide until 2002 onwards, where both regions use tillage as weed control for the years prior to 2002.

Lastly, the nitrogen applied on cropland affects soil nitrous oxide emissions. Holos considers nitrogen from fertilizer, land applied manure, and crop residue; however, these parameters are not collected by the Dairy Cost Study. Differing from Holos defaults, this study assumes that farmers will use manure for fertilizer. If there is insufficient manure for cropping needs, synthetic fertilizer will be used in an amount that is equal to the difference between the available manure nitrogen and the cropping needs suggested by the Holos crop specific nitrogen application rates (Table B.7). For cereal crops, Holos defaults for fertilizer usage are only available for grain production. As such, this study uses the assumption that silage and greenfeed of the same crop will have the same fertilizer application rate as their grain producing counterpart.

If there is excess manure, manure will be applied until the Alberta maximum

[6] South Alberta is defined as Agricultural Regions 1 and 2, while Northern Alberta includes Agricultural Regions 3, 4, 5, 6, and 7.

Table 4.6 Rate of fallow area for agricultural regions in Alberta (%)

Year	South Alberta	North Alberta
1996	41.0%	8.3%
1997	39.3%	8.0%
1998	37.6%	7.7%
1999	35.9%	7.4%
2000	34.2%	7.1%
2001	32.5%	6.8%
2002	30.8%	6.5%
2003	29.1%	6.2%
2004	27.4%	5.9%
2005	25.7%	5.6%
2006	23.6%	5.0%
2007	21.9%	4.7%
2008	20.2%	4.4%
2009	18.5%	4.1%
2010	16.8%	3.7%
2011	15.1%	3.4%
2012	13.4%	3.1%
2013	11.7%	2.8%
2014	10.0%	2.5%
2015	8.3%	2.2%

allowable nitrogen levels for the soil type is reached (AAF 2015c). If there is additional manure beyond that limit, the assumption is made that the extra manure is applied elsewhere. Accordingly, a carbon offset is calculated based on the energy that would have been used to produce the synthetic fertilizer displaced by the manure. For this study, the estimated amounts of manure nitrogen that can be applied before the maximum allowable soil nitrate nitrogen limits are reached are presented in Table 4.7. These values are calculated based on the maximum soil nitrate nitrogen levels for Alberta (AAF 2015c), the agricultural region, and the assumption of a baseline of 33.6

Table 4.7 Maximum manure nitrogen levels that can be applied on cropland

Soil texture	**Soil type**	**Soil nitrate N limit (kg/ha)**
Medium or Fine	Brown	106.48
	Dark Brown	134.5
	Black/Gray	162.53
Coarse (Region 1, 2, 4)	Brown	78.46
	Dark Brown	106.48
	Black/Gray	120.49
Coarse (Region 3, 5, 6, 7)	Brown	50.44
	Dark Brown	78.46
	Black/Gray	92.47

kg/ha of nitrate-nitrogen levels in Alberta soils (derived from AAF 2000, AAF 2016c, and Little et al. 2013). Soil nitrate nitrogen limits are dependent on the proximity to the water table. From comparing the agricultural region map (Appendix F) to the Aquifer Vulnerability Index (AVI) map (AAF 2016a), this study assumes that agricultural regions 3, 5, 6, and 7 are closer to the water table (i.e., have a high AVI), while regions 1,2, and 4 are farther from the water table (i.e., have a low AVI).

For crop residue, Holos algorithms require information on cropping parameters such as above ground residue (AGR) ratio, below ground residue (BGR) ratio, yield ratio, nitrogen concentration of residue, and moisture content. Holos defaults for these parameters are provided for barley, oats, wheat, mixed grain, alfalfa, and hay (Table B.7), and used for this study. For silage and greenfeed, the moisture content is assumed to be 60% (AAF 2017c) and 15% (AAF 2015a), respectively. Other cropping parameters for silage are derived from Legesse et al. (2016), and greenfeed is assumed to have the same yield ratio, AGR ratio, BGR ratio, and residue nitrogen concentration as barley silage (Table 4.8).

Table 4.8 Cropping parameters for silage and greenfeed

Crop	Moisture Content	AGR[a] N conc (kg N/kg)	BGR[b] N conc (kg N/kg)	Yield Ratio	AGR Ratio	BGR Ratio
Barley Silage	0.60	0.007	0.01	0.72	0.13	0.15
Corn Silage	0.60	0.013	0.007	0.72	0.08	0.2
Barley Greenfeed	0.15	0.007	0.01	0.72	0.13	0.15
Oat Greenfeed	0.15	0.006	0.01	0.72	0.13	0.15

[a]Above ground residue
[b]Below ground residue

The usage of straw also affects residue levels. This study assumes that all straw used is from AGR from barley grain crops, where farms not using straw will leave the straw portion as AGR on the field. Assuming swathing and rotary combining, which are common practices in Alberta (AAF 2015b, Vogt 2013), it is calculated that 35% of AGR can be used as straw (McCartney et al. 2006, Little et al. 2013).

4.3.1.1.5 Carbon dioxide from energy use

Energy is used for many farm operations on for the dairy enterprise; for example, for cropping, operating a dairy barn, and feed processing. Emissions from the production of capital goods such as machinery are not included for this study. As this study uses the farm gate as the end boundary, emissions from the transport, processing, and consumption of milk are also not included. Sources of carbon dioxide emissions included in Holos are cropping fuel use, irrigation, herbicide manufacturing, fertilizer manufacturing, manure spreading, and dairy barn operation (Equations A.42 to A.50). Information required for these algorithms include: cropping area, emission factors, fertilizer applied, manure applied, and electricity conversion factor. Various emission and conversion factors (i.e., for energy required to produce fertilizer, spread manure, operate a dairy barn) are provided by Holos. For the electricity conversion factor, Alberta specific factors from Environment and Climate Change Canada (2016) are used, with linear interpolations for the years without specific factors (Table 4.9). In addition, from the trends presented by Statistics Canada (2008), this study assumes irrigation is not used[7] and that herbicide is applied for all observations in the dataset.

Additional to the Holos algorithms above is the inclusion of emissions from processed feed. The Dairy Cost Study collects price and quantity information for the processed feeds: brewer's grain, beet pulp, molasses, dairy ration, protein supplement, calf feed, milk replacer, mineral and vitamins, salt, and alfalfa pellets. For this study, emission factors are used for many of the processed feeds. The emission factors for beet pulp and molasses are derived from Klenk et al. (2012): 0.047 kg CO_2 equivalent per kg beet pulp and 0.179 kg CO_2 equivalent per kg molasses. Based on derivations from Alemu et al. (2017), additional emission factors used in this study are: 0.45 kg CO_2 equivalent per kg calf feed, 0.54 kg CO_2 equivalent per kg mineral supplement, 0.79 kg CO_2 equivalent per kg brew grain, and 0.96 kg CO_2 equivalent per kg protein supplement (Adom et al. 2012, Adom et al. 2013, Gan et al. 2011, Gan et al. 2012, Mogensen et al. 2014, Preston 2010). For milk replacer, an emission factor of 1.38 kg CO_2 equivalent per kg is used (O'Brien et al. 2014). Alfalfa pellets are assumed to have a similar moisture content to alfalfa hay (CCOF 2015), and 30 KWh/tonne alfalfa is assumed for the pelleting process (Tabil and Sokhansanj 1996). As the Dairy Cost

[7] Irrigation of cereal and forage crops may be a common practice for some counties in Southern Alberta; however, looking at the Southern Alberta regions (agricultural regions 1 and 2) as a whole, less than 15% of cropland is irrigated (Statistics Canada 2008)

Table 4.9 Electricity emission factor in Alberta

Year	Electricity Emission Factor (g CO2eq/kWh)
1996	1000
1997	1000
1998	1000
1999	1000
2000	1000
2001	1000
2002	1000
2003	1000
2004	1000
2005	990
2006	1000
2007	1000
2008	1000
2009	1000
2010	1100
2011	1000
2012	930
2013	810
2014	820
2015	820
2016	820

Study does not provide the components of dairy ration, it is assumed to be 80% barley and 20% protein supplement (adapted from Robinson 2016).

4.3.1.1.6 Summary of greenhouse gas emissions estimates

Average dairy farm GHG emissions, calculated over all the observations in the study sample, are presented in Table 4.10. To calculate GHG emissions in terms of CO_2 equivalents, the Holos default global warming potentials are used: CO_2 = 1, CH_4 = 25, N_2O = 298. This study uses Holos algorithms adapted to specific Alberta conditions to calculate dairy farm GHGs, and the GHG results in this study are similar to those from

Table 4.10 Mean value (across all observations) and the proportional representation of different types of GHG emissions

Emission type	**Mean value (kg CO_2 equivalent/farm/year)[a]**	**Proportion of total**
Cropping N_2O	86516.90	0.0912
Enteric CH_4	469585.69	0.4950
Manure CH_4	109590.14	0.1155
Manure N_2O	69617.63	0.0734
Energy CO_2	213298.61	0.2249
Total emissions	948608.96	

[a]The global warming potentials assumed by this study follow Holos defaults: CO_2 = 1, CH_4 = 25, N_2O = 298

other Canadian studies. Both McGeough et al. (2012) and Vergé et al. (2007) found enteric methane to comprise almost 50% of total emissions, compared to 49.5% for this study. Cropping and manure emissions from this study, at 9% and 19% respectively, are lower than their range of 15-30% (McGeough et al. 2012, Vergé et al. 2007). This is likely due to the higher energy emissions in this study, which make up 22% of total farm emissions. One possible explanation is that energy generation in Alberta is more carbon intensive energy than other provinces (Energy and Climate Change Canada 2016), contributing to higher energy emissions.

The GHG intensity, or the GHG emissions per litre of milk, from the results of this study is also similar to other Canadian studies. Vergé et al. (2007) estimated that for the Canadian prairie provinces, 1.15 kg of CO_2 equivalents are emitted for every litre of milk, while McGeough et al.'s (2012) life-cycle assessment for a sample Quebec dairy farm predicted that 0.92 kg of CO_2 equivalents are emitted per liter of milk produced. For this study, the average value over all sample observations is 1.35 kg of CO_2 equivalents per liter of milk, which is slightly higher than the previous studies, and it is likely because this study also includes emissions from dairy animals meant for livestock sales.

4.3.1.2 Milk output

Milk produced from the farm is one of the two good outputs used in this study. Fat and protein corrected milk (FPCM) is used because the value of milk varies with its components. Milk output is standardized to 4% fat and 3.3% protein following methodology from the International Dairy Federation (IDF 2010):

$$FPCM\ =\ Production * (0.1226 * Fat\% + 0.0776 * Protein\% + 0.2534) \tag{4.9}$$

Milk production is the sum of quota milk, over quota milk, other milk, and milk fed to livestock. Fat percentage is obtained from the Dairy Cost Study, while milk protein percentage is assumed to be equal to the provincial average in Alberta of 3.3% (Alberta Milk 2010).

4.3.1.3 Livestock output

The second beneficial output is livestock produced, represented by implicit quantity of livestock sold. This variable is constructed through dividing total livestock sales by the implicit price. Following Hailu et al. (2005) and Dayananda (2016), the implicit price used in this study is calculated using the Fisher Price Index (FI), with sales aggregated across all animal categories. The number and price of animals sold are provided by the Dairy Cost Study, under the animal categories: cows, bred heifers, young heifers, heifer calves, bull calves, and bulls.

Using 1996 as the base year, FI is defined:

$$FI_{it} = \sqrt{LI_{it} * PI_{it}} \tag{4.10}$$

where LI is the Laspeyres Index:

$$LI_{it} = \frac{P_{it}Q_{1996}}{P_{1996}Q_{1996}} \tag{4.11}$$

and PI is the Paasche Index:

$$PI_{it} = \frac{P_{it}Q_{it}}{P_{1996}Q_{it}} \tag{4.12}$$

The base year price (P_{1996}) and quantity (Q_{1996}) are the average of the prices and quantities, respectively, for all farms in 1996.

4.3.2 Inputs

4.3.2.1 Forage input

Similar to livestock output, an implicit quantity of forage is calculated and used to represent forage input. A FI with 1996 as the base year is used to aggregate the different forage types into an implicit price (Equations 4.9, 4.10, and 4.11). Total spending on forage, including purchased and homegrown feed, is divided by the FI to obtain an implicit quantity. The homegrown price of feed is assigned by the Dairy Cost Study based on regional market values. For this study, forage includes: hay, alfalfa pellets, straw, silage, and greenfeed. Prices and quantities of these forages are collected by the Dairy Cost Study.

4.3.2.2 Concentrate input

The variable for the concentrate input is constructed in the same manner as for the forage input. For this study, concentrate includes barley, oats, mixed grain, supplement, dairy ration, milk replacer, calf feed, salt, minerals and vitamins, molasses, beet pulp, and brewer's grain. Prices and quantities of these feeds are obtained from the Dairy Cost Study.

4.3.2.3 Capital input

For this study, the quantity of capital is proxied by the annual cost of capital (Equation 4.13).

$$Capital\ cost\ =\ \sum_{c}^{C}(Asset\ value_c\ *\ User\ cost_c)\ +\ Repairs\ +\ Rent \qquad (4.13)$$

The user cost for each type of capital (c) is calculated following Slade and Hailu (2016):

$$User\ cost_c\ =\ interest_c + depreciation_c + tax_c \qquad (4.14)$$

The user cost represents the "price" of capital, and is expressed as a decimal form as opposed to a percentage. Taxes are assumed to be negligible for all types of assets. Depreciation values are calculated by the Dairy Cost Study based on the type of asset and the original value of the asset. The interest is derived following Slade and Hailu (2016):

$$interest_c\ =\ [(1-g) * r_e] + [g * r_d] \qquad (4.15)$$

where g is the debt to asset ratio for the dairy enterprise, r_e is the cost of equity, and r_d is the cost of debt. A value for g is calculated by dividing total capital loans over the total value of capital assets, both obtained from the Dairy Cost Study. The cost of equity is proxied using the 5-10 year marketable Government of Canada bond rate (Statistics Canada 2017c). The cost of debt is the implicit interest rate derived from Dairy Cost Survey data through dividing interest payments by the value of capital loans.

For asset values, investments into machinery, dairy equipment, other equipment, dairy buildings, land, and dairy animals are considered for this study. Market values for these categories are provided by the Dairy Cost Study. Specifically, the market values are based on average annual market price (i.e., for livestock) or by updating the original investment value with inflation factors and depreciating accordingly. For the Dairy Cost Study, machinery includes tractors and trucks; dairy equipment includes bulk tanks, pipelines, washers, pumps, and generators; other equipment includes manure spreaders, trailers, barn cleaners, bale feeders, silo unloaders, feed mixers, fans, small tools (ex: saws, drills), and computers; buildings include barns, sheds, feed bunkers, corrals, calf and hutches; land is the acreage for pasture, houses, dairy buildings, and corrals not including farmland; and value of dairy animals is the yearly average of the total value of lactating cows, dry cows, heifers, bulls, and calves. Repair and rental fees are also provided by the Dairy Cost Study.

4.3.2.4 Labour input

The Dairy Cost Study collects data on hours of paid, family, and operator labour. An FI is not used for labour due to potential measurement error from assuming a price for family and operator labour. As such, the sum of the hours of paid, family, and operator labour is used as the labour input variable.

4.3.2.5 "Other" input

The “other” input variable includes expenditures for inputs such as insurance, bedding, veterinary expenses, utilities, milk hauling and miscellaneous expenses.

Similar to forage and concentrate, an implicit quantity is calculated from dividing total expenditure by an implicit price, where the implicit price is the FI with the base year as 1996. Price information is required for the FI; as prices are not available in the dataset, two types of price indices are substituted– the Farm Input Price Index (Statistics Canada 2017d) and the Consumer Price Index (Statistics Canada 2018). From the Farm Input Price Index, the price index for general business costs is used for the "miscellaneous" and "taxes and insurance" categories in the Dairy Cost Study, and the price index for animal production is used for "feed processing", "bedding and supplies", "breeding costs", and "veterinary and medicine". From the Consumer Price Index, the gasoline price index is used for "milk hauling", the utilities index for "utilities", and the fuel oil and other fuels index for "fuel".

4.3.3 Inefficiency model variables

Variables included in the inefficiency model are selected based on insights from previous studies as well as availability in the data set. Typical variables included in past efficiency studies include farming intensity, livestock quality, age and education of farmer, and access to technology (e.g., Jiang and Sharp 2015, Mosheim and Lovell 2009, Weersink et al. 1990). For this study, the variables included in the model are herd size, milk yield, butterfat, years farming, proportion of paid labour, proportion of purchased feed, debt to asset ratio, a regional dummy for a farm located in North or South Alberta, linear and quadratic time trends, and proportion of forage in the diet. All of these variables are derived from data collected by the Dairy Cost Study.

Herd size is measured as the number of lactating and dry cows, and is hypothesized to have a positive effect on efficiency due to scale effects. Milk yield (litres of FPCM per cow per day) directly reflects the productivity of the cow and is expected to be positively related to farm efficiency. Butterfat percentage is also expected to have a positive effect, as it can reflect management ability, especially as dairy quota is calculated in kg of butterfat (Alberta Milk 2017c). Years farming and the time trend are hypothesized to have a positive effect on efficiency due to benefits of increased experience and technological improvements, respectively. A higher proportion of paid labour or purchased feed is predicted to negatively affect efficiency, because operator labour and homegrown feed, especially forages, is predicted to be higher quality than their purchased counterparts. Debt to asset ratio is expected to have a negative effect on efficiency as it can impose constraints on capital acquirement. A regional dummy is also included, since farms in Southern Alberta have different farming practices and environmental factors; for example, southern producers feed more corn silage compared to producers in Northern Alberta (Statistics Canada 2014b). Lastly, the proportion of the forage in the diet is considered, which is predicted to have negative effect on efficiency as forage is a lower energy feed relative to concentrate, and is associated with higher enteric methane emissions (Beauchemin et al. 2008).

4.4 Results

4.4.1 Descriptive statistics

Descriptive statistics for the variables used in the frontier and inefficiency model are presented in Table 4.11.

Table 4.11 Descriptive statistics for model variables (n = 1075)

	Name	Mean	Std. Dev.	Min	Max
Desirable Outputs	Milk output (hL FPCM[a])	7222.42	5427.88	1178.07	41335.22
	Livestock output[b]	31493.85	45046.93	0.00	683970.10
Detrimental Output	GHG (kg CO_2 eq)	948609.00	737528.30	229067.50	6418104.00
Inputs	Forage[b]	106721.80	96297.20	14145.00	947044.40
	Concentrate[b]	185747.50	145387.70	21160.65	1058836.00
	Labour (hours)	6101.16	3574.99	1369.88	35542.00
	Capital[c]	1318898.50	2719137.71	63576.98	30380290.07
	Other[b]	76963.06	57111.89	16239.74	583759.80
Inefficiency Model Variables	Milking herd size (number of cows)	111.90	86.42	26.58	728.75
	Milk yield per cow (L FPCM/day)	17.68	3.12	1.18	25.83
	Butterfat (%)	3.74	0.26	2.68	5.19
	Years farming	19.63	11.60	0.00	57.00
	Paid labor proportion of total	0.2413	0.26	0.00	0.92
	Purchased feed, proportion of total	0.6407	0.21	0.03	1.00
	Debt to asset ratio	0.0201	0.02	0.00	0.12

Proportion of forage in diet	0.3783	0.10	0.12	0.75
North/South dummy (North = 1)	North = 501 observations		South = 574 observations	

[a]Fat and protein corrected milk, where milk is standardized to 4% fat and 3.3% milk protein (IDF 2010)
[b]The quantity is the implicit quantity obtained by dividing the value of sales (or expenses) by the implicit price (Fisher Price Index with 1996 as the base year)
[c]The quantity of capital is proxied by the annual cost of capital (see Section 4.2.3.3)

4.4.2 Technical properties of the frontier

To examine the impact of considering GHG emissions on the economic performance of farmers, results from two versions of the enhanced hyperbolic distance function are compared; one including GHGs as a detrimental output and one without GHGs. To prevent problems with model convergence, the production frontier variables are normalized by their geometric mean. Due to the presence of econometric issues (i.e., autocorrelation), bootstrapped standard errors generated with 2000 replications are used. The parameter estimates for both models are reported in Table 4.12.

For the no GHG model, the first order coefficients for the inputs and outputs are statistically significant and have the expected signs. Similar results are present for the GHG model, with the exception of the first order coefficient for forage, which is not statistically significant. Looking at the fit of the models, a likelihood ratio test reveals that the additional GHG parameters significantly improve the fit of the model ($p < 0.001$). For SFA, the additional parameters σ_v^2 and σ_u^2 are also estimated. Both the variance of the stochastic error term and the variance of the inefficiency term are statistically significant, suggesting stochastic and inefficiency effects exist in the sample. As such, an SFA

Table 4.12 Maximum likelihood parameter estimates: Hyperbolic distance function with and without GHGs (n = 1075)

	GHG		Without GHG	
	Estimate[a]	Std. Error[b]	Estimate[a]	Std. Error[b]
Intercept	-0.0090	0.0152	0.0822***	0.0159
Forage[c]	0.0116	0.0088	-0.0376***	0.0118
Concentrate	-0.0241***	0.0089	-0.0706***	0.0108
Capital	-0.0483***	0.0119	-0.1916***	0.0106
Labour	-0.0251***	0.0069	-0.0514***	0.0091
Other	-0.0350***	0.0075	-0.0834***	0.0097
Livestock sales	0.0174***	0.0057	0.0244***	0.0073
Linear time trend	-0.0062**	0.0025	-0.0117***	0.0027
Quadratic time trend	-0.0002	0.0001	-0.0006***	0.0001
LivestockSales*LivestockSales	0.0024	0.0160	0.0046	0.0143
LivestockSales*Forage	-0.0782***	0.0192	-0.0145	0.0220
LivestockSales*Concentrate	0.0057	0.0235	-0.0112	0.0263
LivestockSales*Labour	-0.0100	0.0156	-0.0079	0.0169
LivestockSales*Capital	0.0413	0.0267	0.0060	0.0285
LivestockSales*Other	0.0268***	0.0100	-0.0100	0.0117
Forage*Forage	-0.0330	0.0222	0.0310	0.0252
Forage*Concentrate	-0.0360***	0.0108	-0.0207	0.0134
Forage*Labour	0.0248	0.0206	0.0392*	0.0233
Forage*Capital	0.0045	0.0179	-0.0247	0.0234
Forage*Other	0.0503***	0.0133	0.0606***	0.0173
Concentrate*Concentrate	-0.0024	0.0273	-0.0412	0.0333
Concentrate*Labour	0.0167*	0.0097	0.0207**	0.0096
Concentrate*Capital	-0.0451***	0.0172	-0.0741***	0.0239
Concentrate*Other	0.0586***	0.0163	0.0433*	0.0231
Labour*Labour	0.0078	0.0056	0.0078	0.0071
Labour*Capital	-0.0030	0.0142	0.0142	0.0166
Labour*Other	-0.0137	0.0130	0.0004	0.0146
Capital*Capital	-0.0750***	0.0250	-0.0700**	0.0299
Capital*Other	0.0137	0.0122	0.0224	0.0185

Other*Other	-0.0129	0.0163	0.0189	0.0200
GHG	-0.3642***	0.0201		
GHG*GHG	0.0214	0.0533		
GHG*Livestock	0.0754***	0.0291		
GHG*Forage	0.0306	0.0456		
GHG*Concentrate	0.0809**	0.0315		
GHG*Labour	-0.0312	0.0435		
GHG*Capital	0.0009	0.0296		
GHG*Other	-0.1279***	0.0456		
Joint inefficiency model				
intercept	0.5416***	0.0676	0.6803***	0.1015
Herd size	0.0001	0.0001	0.0001	0.0001
Milk yield	-0.0281***	0.0020	-0.0333***	0.0038
Linear time trend	0.0063	0.0040	0.0013	0.0041
Quadratic time trend	0.0000	0.0002	0.0005**	0.0002
Butterfat	-0.0063	0.0149	-0.0429*	0.0242
Years farming	0.0005	0.0004	0.0010**	0.0005
Proportion of paid labour	0.0060	0.0134	0.0182	0.0173
Proportion of purchased feed	0.0072	0.0150	0.0698**	0.0283
Debt to asset ratio	0.0588	0.2097	0.5159	0.3202
North/South dummy (North = 1)	0.0153**	0.0063	0.0010	0.0095
Proportion of forage in diet	-0.1703***	0.0577	-0.0857	0.0837
σ_u^2	0.0023***	0.0007	0.0038***	0.0012
σ_v^2	0.0005***	0.0001	0.0013***	0.0002
Log likelihood ratio	1961.982		1619.716	

[a] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b] standard errors derived from bootstrapping with 2000 replications
[c] with the exception of the intercept, inefficiency model variables, and time trends, the variables are natural logarithms

approach may be more appropriate than a deterministic approach when measuring the efficiency of dairy farms in Alberta.

As the data are normalized by the mean, production elasticities evaluated at the mean can be derived from the first order coefficients (Mosheim and Lovell 2009) (Equations 4.16 to 4.18).

$$\varepsilon_{M,k} = \frac{\partial ln\, y_M}{\partial ln\, x_k} = -\alpha_k \tag{4.16}$$

$$\varepsilon_{m,k} = \frac{\partial ln\, y_m}{\partial ln\, x_k} = -\frac{\alpha_k}{\beta_m} \tag{4.17}$$

$$\varepsilon_{b,k} = \frac{\partial ln\, b}{\partial ln\, x_k} = -\frac{\alpha_k}{\delta} \tag{4.18}$$

A summary of the production elasticities is provided in Table 4.13. Input production elasticities for milk and livestock outputs have consistent signs and statistical significance. However, the livestock production elasticities are much higher (numerically) than the milk production elasticities, for both the GHG and without GHG models. Overall, milk production elasticities are low, with a sum of 0.435 for the no GHG model, suggesting decreasing returns to scale. Mbaga et al. (2003) found similar values for milk production elasticities; their study estimated elasticities around 0.18 for both concentrate and capital, 0.08 for labour, and 0.04 for forage. Comparing with this study, milk production elasticities not considering GHGs are 0.19 for capital, 0.07 for concentrate, 0.05 for labour, and 0.04 for forage. On the other hand, the livestock production elasticities display increasing returns to scale, with a sum of 17.8, suggesting an 1% increase in all inputs will increase livestock production by almost 18%. The

Table 4.13 Production elasticities for estimated models (with and without GHG)[a,b,c]

	Model	Forage	Concentrate	Labour	Capital	Other
Milk	With GHG	-0.012 (0.0088)	0.024*** (0.0089)	0.025*** (0.0069)	0.048*** (0.012)	0.035*** (0.0075)
	Without GHG	0.0376*** (0.012)	0.071*** (0.011)	0.051*** (0.0091)	0.192*** (0.011)	0.083*** (0.0097)
Livestock	With GHG	-0.666 (0.42)	1.384*** (0.505)	1.441*** (0.500)	2.769*** (0.752)	2.005*** (0.621)
	Without GHG	1.541*** (0.504)	2.894*** (0.698)	2.107*** (0.579)	7.847*** (1.645)	3.415*** (0.806)
GHG	With GHG	0.0319* (0.0182)	-0.0663*** (0.0204)	-0.0690*** (0.0176)	-0.133** (0.0267)	-0.0960** (0.207)

[a] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b] The elasticities presented here represent the % increase in output from a one % increase in a specific input.
[c] Standard errors are presented in parentheses

responsiveness of livestock production to increased input use is likely due to production decisions focusing on dairy revenue rather than on the value of livestock production.

Between the GHG and no GHG models, the milk and livestock production elasticities follow a similar pattern with respect to sign and significance, with the exception of the elasticity for forage. Specifically, the production elasticities for inputs other than forage are positive and statistically significant at the 1% level. The elasticities are also consistently larger for the non-GHG model (i.e., when GHGs are not held constant). This suggests that the marginal productivity of inputs are constrained if a certain level of GHGs is maintained. This effect is similar across the milk output and the livestock output– milk production elasticities for the no GHG model are between 2.0–4.0 times higher than for the GHG model, while livestock production elasticities for the no GHG model are 1.5–2.9 times higher than the GHG model. For both outputs, when the constraint of maintaining a constant level of GHGs is added, productivity is the most limited for capital, and the least limited for labour, suggesting that if an environmental goal is to be reached, increasing production of beneficial outputs through labour may be more effective than through increasing capital. This may be due to the fact that labour is a non-material input, and that livestock input is aggregated into the capital input, given that enteric methane comprises the bulk of GHG emissions (Table 4.10).

For the forage input, both the sign and significance of the production elasticity differs between the GHG and no GHG models (Table 4.13). If GHG emissions are not considered, a 1% increase in forage will increase milk output by 0.038% (evaluated at the mean). However, when GHGs are included in the model, a 1% increase in forage input, for a given level of emissions, does not have a statistically significant effect on milk production. This difference (i.e., shifting from significantly positive to insignificantly negative) is likely due to the contribution of forage to higher enteric methane emissions (Boadi et al. 2004).

In the case of the production elasticities for the detrimental output, a 1% increase in forage will increase GHG emissions by 0.032%. This is not surprising given the relationship (noted earlier) between forage consumption and enteric methane emissions. The GHG production elasticities for the other inputs are all negative; an increase in any of these inputs decreases GHG emissions. The decrease in GHGs is expected for non-material inputs such as labour and "other", since use of these inputs is not typically associated with production of emissions. In addition, increased labour and "other" inputs can be used towards animal care, and improved animal health is a large contributor to increased milk yield and reduced overall environmental impact (Weiske et al. 2006). For capital, which has the largest marginal effect on GHG reduction, it may be the case that investing in machinery and equipment can contribute to more efficient feeding, milking, and general farm operations. Similarly, an increase in concentrate, keeping all other inputs and outputs constant, is predicted to decrease GHG emissions. While concentrate is a material input, it has been found that increasing concentrate in the diet can reduce the feed energy that is converted to methane due to the resulting decrease in ruminal pH (Beauchemin et al. 2008).

4.4.3 Efficiency estimates

For simplicity, the efficiency from the model estimated with GHGs is denoted environmental efficiency (EE) and the efficiency from the model without GHGs as technical efficiency (TE). The efficiency estimates are summarized in Table 4.14. Efficiencies from the models with and without GHGs are very similar, as seen in the scatterplot (Figure 4.1), with a mean environmental efficiency of 0.9252 and a mean technical efficiency of 0.9367. In addition, the two distributions of efficiencies are highly correlated, both in terms of their linear relationship (i.e., Pearson's correlation coefficient is 0.8638) and their rank (i.e., Spearman's correlation coefficient is 0.8367).

Further highlighting the similarity between TE and EE is their relationship to GHG intensity, that is, the GHG emissions per litre of milk (Figures 4.2 and 4.3). As the definition of environmental efficiency used in this study is a more holistic measure that includes both environmental and economic factors, the efficiency measures can also be compared to a more environmentally focused measure, or the GHG intensity. Both efficiency measures show a moderate negative linear relationship with GHG intensity;

Table 4.14 Efficiency results: Descriptive statistics

Model	Mean	Std. Dev.	Min	Max
With GHG	0.9367	0.0453	0.7599	0.9948
Without GHG	0.9252	0.0545	0.6922	0.9925

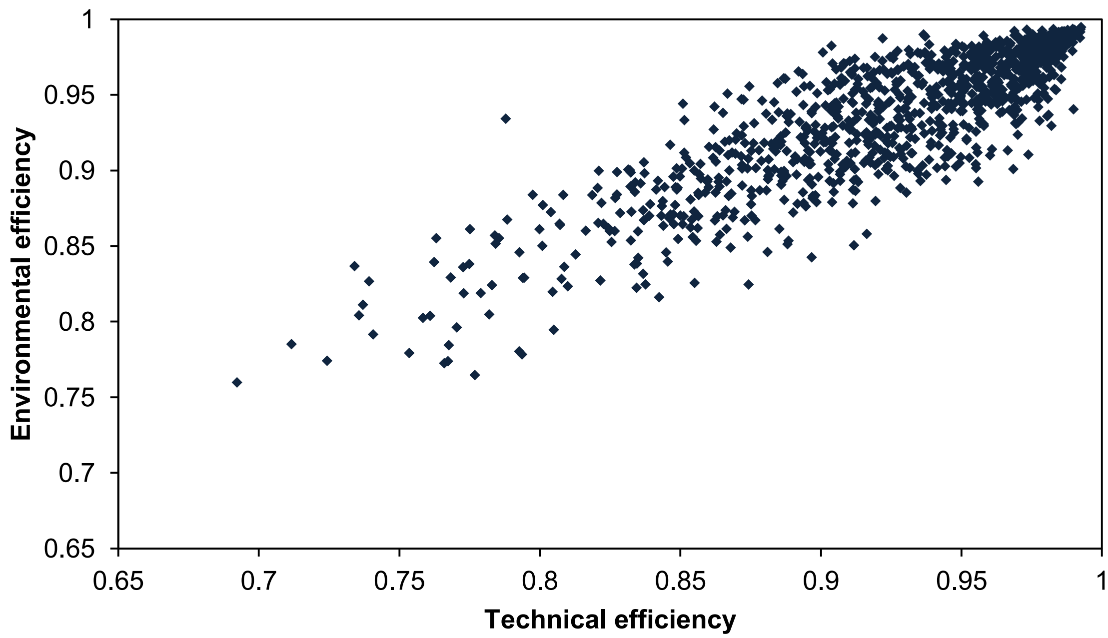

Figure 4.1 Scatterplot of technical efficiency and environmental efficiency

as technical and environmental efficiency increase, GHG emissions per litre of milk produced decreases, with EE having a stronger relationship– the Pearson's correlation coefficient for EE is -0.607 while it is -0.478 for TE. In addition, it can be seen that lowest GHG emitting farms are concentrated at the frontier for both TE and EE. Overall, it appears that minimizing GHG emissions aligns with the objective of maximizing output for given levels of inputs.

One possible explanation of the close relationship between TE and EE is that GHG emissions are in part attributable to inefficient use of energy by the animal. Enteric

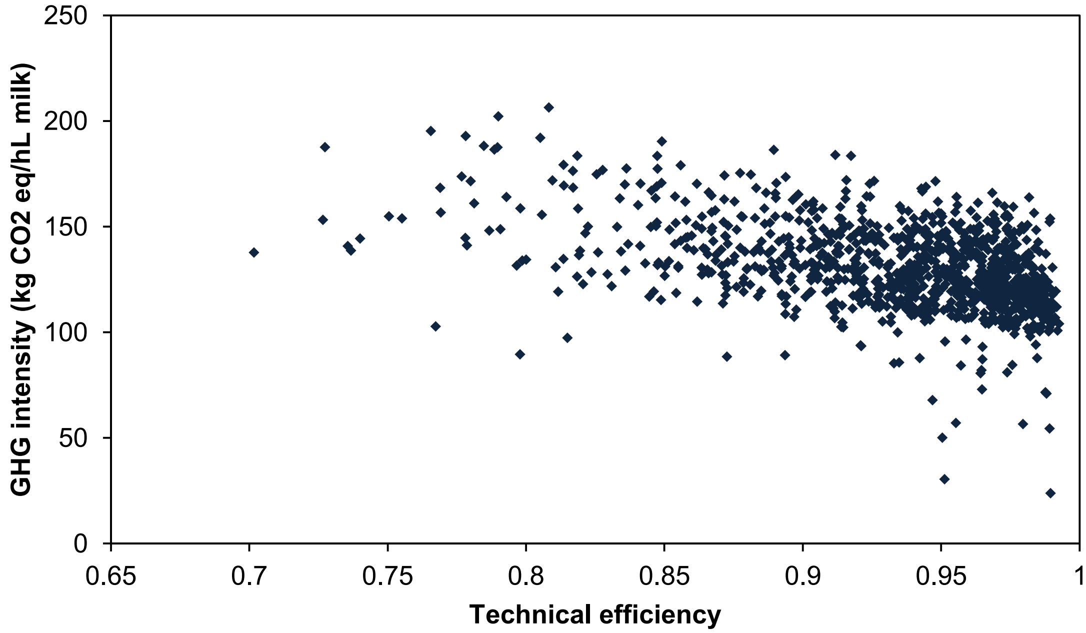

Figure 4.2 Scatterplot of technical efficiency and the GHG intensity of milk production

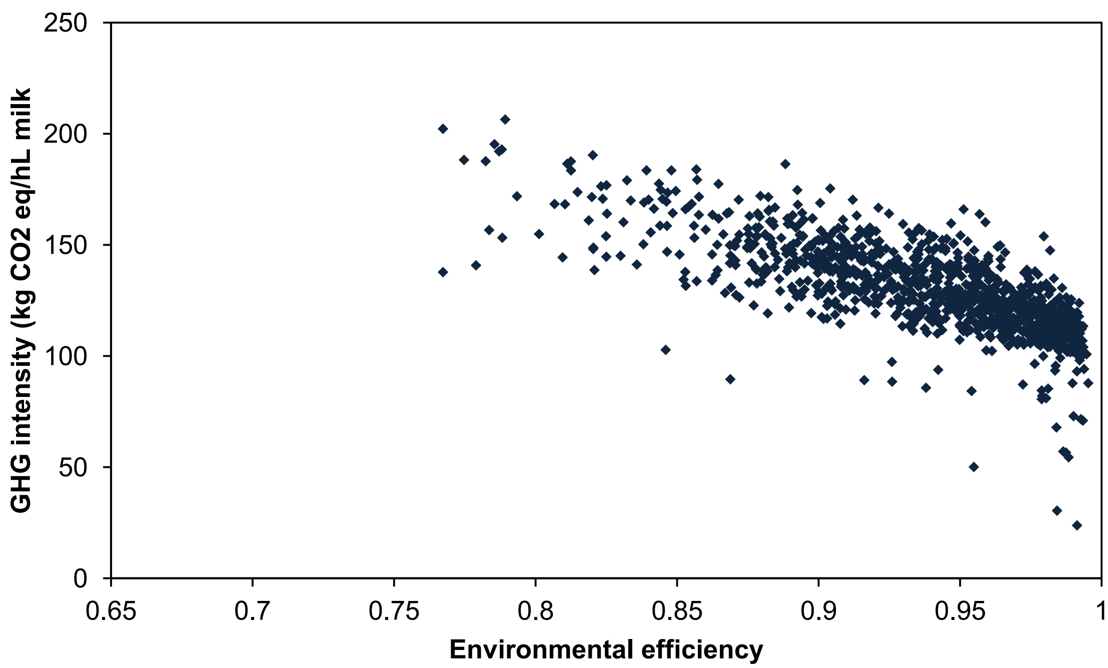

Figure 4.3 Scatterplot of environmental efficiency and the GHG intensity of milk production

methane, for example, makes up the largest proportion of the GHG emissions (Table 4.10) and represents a significant loss in feed energy that could have been converted to productive outputs. This contribution to GHG emissions could therefore be reduced with more efficient energy use by the cow. Previous studies have also found high correlation between environmental and technical efficiencies for dairy operations, with Spearman rank correlations ranging from 0.418 to 0.920 (Dayananda 2016, Reinhard et al. 1999, Shortall and Barnes 2013).

The average efficiency level for the sampled Alberta dairy farms is very high, suggesting that many of the surveyed Alberta dairy farms are close to the frontier. This result is consistent with many previous dairy technical efficiency studies. For example, Mbaga et al.'s (2003) study of Quebec dairy farmers tested a variety of SFA models and found average scores to be approximately 0.95. The high proportion of dairy farmers close to the frontier is suggested to be a result of the stability of supply management (Mbaga et al. 2003). Similarly, Mamardashvili et al. (2016) estimated an average environmental efficiency level of 0.966 for Swiss dairy farms using an enhanced hyperbolic distance function approach. Bokusheva and Kumbhakar's (2014) study had an average TE of 0.928 for Dutch dairy producers, and Cabrera et al. (2010) found an average technical efficiency score of 0.88 for Wisconsin dairy farmers. The flexibility inherent in the enhanced hyperbolic function may also contribute to higher efficiency scores as adjustments to inputs, desirable outputs, and undesirable outputs are all considered (Cuesta et al. 2009, Mamardashvili et al. 2016).

While average technical efficiency and environmental efficiency values are numerically similar, the mean efficiency scores are significantly different ($p < 0.001$) in statistical terms. Overall, when considering GHGs, Alberta dairy farms have the potential to increase milk and livestock outputs by 6.82% ($\frac{1}{0.9361} - 1 = 0.0682$), while simultaneously reducing input use and GHG emissions by 6.39% ($1 - 0.9361 = 0.0639$).

4.4.4 Factors affecting efficiency

The inefficiency model parameter estimates for both versions of the distance function (i.e., with and without GHG emissions) are also presented in Table 4.12. Given the structure of the inefficiency model, positive coefficients indicate that the variable contributes positively to inefficiency (u_i); that is, variables with positive coefficients are negatively related to technical or environmental efficiency. From Table 4.12, it can be seen that the signs on coefficients are consistent between the two versions of the inefficiency model. However, there are differences between the two inefficiency models in terms of statistical significance. The only variable statistically significant for both environmental efficiency and technical efficiency is milk yield per cow. Consistent with previous studies (e.g., Weersink et al. 1990), increased milk yield per cow is positively related to efficiency. Higher milk productivity is likely due to improved feeding, management, and breeding practices. There are also differences in the inefficiency model results when compared with other studies (e.g., Cabrera et al. 2010, Mosheim and Lovell 2009, Weersink et al. 1990) in that herd size, proportion of paid labour, and debt-to-asset ratio have no statistically significant effect on efficiency.

Variables significant for technical efficiency but not environmental efficiency are butterfat, years farming, and proportion of purchased feed. As expected, increased butterfat percentage is positively related to technical efficiency; however, it does not have a significant effect on environmental efficiency. One possible reason for this difference is the butterfat component requires more energy to produce, which can lead increased feed intake and higher GHG emissions (i.e., through cropping and enteric methane) (Boadi et al. 2004, Johnson and Johnson 1995). Years of farming (i.e., experience) is negatively related to technical efficiency. A possible explanation is younger farmers may be more aware of new innovations and technology that facilitate improved technical efficiency, but that these may not necessarily result in a smaller carbon footprint. Similar to Weersink et al.'s (1990) study, greater use of purchased feed is negatively related to technical efficiency, which their study suggests could be a result of homegrown feed being of higher quality compared to purchased feed.

Conversely, the regional dummy and proportion of forage in the diet are significantly related (in statistical terms) to environmental efficiency but not technical efficiency. The result for the regional dummy suggests that farms in northern Alberta are less environmentally efficient than those in southern Alberta, although there is no statistically significant difference in their technical efficiency. Southern farms may have a smaller environmental impact due to differences in soil, feeding practices (e.g., producers in southern Alberta feed more corn silage, which has more than double the average yield of barley silage (Kosinski 2012)), and temperatures (which can affect factors such as crop yields, milk yields, and cattle maintenance energy requirements). The proportion of forage has the opposite sign than expected, where increasing forage will increase environmental efficiency with no statistically significant effect on technical efficiency. This is unexpected as high forage diets are associated with greater enteric methane emissions (Boadi et al. 2004). However, there may be other aspects of feeding higher forage that can improve environmental efficiency; for example, differences in cropping practices, improved animal health, and reduced fertilizer and energy use (Boadi et al. 2004). In addition, the use of proportionally more forage in the diet for a given level of milk production is likely accomplished through feeding higher quality forages. There is evidence that increased forage quality (and specifically digestibility) results in reduced GHG emission intensity in ruminants (e.g., Beauchemin et al. 2011, Guyader et al. 2017, Knapp et al. 2014).

4.4.5 Shadow prices

As there is no market for GHGs, the duality between distance functions and revenue and profit functions is exploited to derive the shadow price of GHGs. The shadow price can be interpreted as the opportunity cost of reducing GHGs where the marginal rate of transformation between the good outputs and GHGs is valued in economic terms. Following Vardanyan and Noh (2006) and Mamardashvili et al. (2016), the shadow price (s_m) for the mth beneficial output can be calculated as:

$$s_m = -p_m \frac{\frac{\partial D_H}{\partial b}}{\frac{\partial D_H}{\partial y_m}} \tag{4.19}$$

where p_m is the price of the beneficial output. As the data used in this study are normalized, the resulting shadow prices are representative of the mean of the data rather than at the frontier. However, given that mean efficiency is very high, the marginal rate of transformation at the mean should be similar to that for the frontier.

Table 4.15 reports the output prices and shadow prices. Using the average price of milk received by the sampled Alberta dairy farmers standardized to 2015 Canadian dollars, it is estimated that the opportunity cost of reducing GHG emissions in terms of foregone milk revenue is $308.29 per tonne of emissions (in terms of CO_2 equivalents). Previous studies have estimated the shadow price of GHGs from dairy farms. For example, Wetteman and Latacz-Lohmann (2017) estimated the abatement cost (using DEA) to be €165 per tonne, equivalent to approximately $234 in 2015 Canadian dollars (Bank of Canada 2018). Using a parametric directional distance function approach, Njuki and Bravo-Ureta (2015) found a range of shadow prices from $43/tonne to $950/tonne for different counties across the United States. From these results it can be seen that there is no consensus on the opportunity cost of reducing emissions, and Vardanyan and Noh (2006) suggests it is due to the sensitivity of shadow price estimates to model choice (i.e., functional form and directional vectors). The shadow value from this study is within the range found by Njuki and Bravo-Ureta (2015), although towards the higher end. This may be attributable to slightly higher dairy prices in Canada. As such, pollution reduction can be a costly endeavour for dairy farmers, especially those close to the frontier.

A shadow price of GHGs is also derived for livestock production (Table 4.15); that is, the opportunity cost of GHG abatement in terms of the value of the sale of livestock by the dairy producer. Using the average selling price of livestock (i.e., total livestock revenue divided by total units of livestock sold) in the study sample standardized to 2015, the opportunity cost is $895.84 of foregone livestock revenue per tonne of GHG emission reduced. The large discrepancy in shadow values between the two beneficial outputs (milk and livestock) suggests that Alberta dairy farmers are not allocatively efficient. It would be expected that producers who are allocatively efficient

Table 4.15 Shadow prices for livestock and GHG outputs[a,b]

Output	Model	Market Price[d]	Shadow prices[c] Livestock ($)	Shadow prices[c] GHG (tonnes)
Milk	GHG	$111.95/hL	- $0.37*** (0.12)	$308.29*** (17.01)
	Without GHG		- $0.52*** (0.16)	---
Livestock	GHG	$603.41/head	---	$895.84*** (123.15)
	Without GHG		---	---

[a] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b] Standard errors are presented in parentheses
[c] The shadow price is the value of the output in the leftmost column given up for a one unit reduction of the outputs in the right hand columns
[d] Prices are adjusted to 2015 price index (Statistics Canada 2017b)

would have equal shadow prices associated with both outputs (Mamardashvili et al. 2016). The discrepancy between the two shadow prices may be due to the focus of management efforts being on the dairy enterprise instead of livestock production, since livestock revenue would likely be considered a "by-product" for many commercial dairy operations. The livestock shadow price is also higher than the milk shadow price, which is similar to the results of Mamardashvili et al. (2016). In that study, non-milk output was estimated to have a higher shadow price than milk output. A possible reason for this pattern is that more inputs associated with livestock production may be less substitutable, creating constraints that make it more costly to reduce GHG emissions. This would be similar to findings by Arandia and Aldanondo-Ochoa (2011) for organic farms; specifically, they found higher shadow prices for organic farms than for conventional operations, which they attribute to the effect of additional regulatory restrictions.

The opportunity cost between milk and livestock production can also be calculated, and unlike the GHG shadow price, the livestock shadow price is negative. Further reduction of GHGs at the frontier will require diversion of inputs from the beneficial outputs, decreasing potential revenue. However, reduction of livestock output may increase available inputs for milk production, potentially leading to higher milk revenue. The no GHG model predicts a $0.52 increase in milk revenue per dollar of livestock revenue reduced, which is higher than the price of $0.37 predicted by the GHG model. The lower potential milk revenue when GHGs are held constant suggests that when inputs are used for milk production compared to livestock production, GHG emissions can increase. A possible explanation is that the majority of livestock sales are from the sale of cows (i.e., cows comprise an average of 73% of total livestock sales across the entire sample); these sales are likely from cull cows, where there will be lower consumption of feed and other inputs compared to high producing lactating cows.

4.5 Sensitivity Analysis

The GHG estimates in this study have a wide range of uncertainty– in addition to the simplifying assumptions used, Holos also predicts a range of uncertainty of < +/- 40% for calculated GHG emissions. To evaluate the effect of this uncertainty on the efficiency estimates of GHG emissions, a basic sensitivity analysis is performed. Firstly, the main assumptions behind the GHG emissions for this study are modified to see how the GHG emissions will change, and the results are presented in Table 4.16. Overall, changing the assumptions minimally affects the rank correlation between the original and modified GHG emissions. However, the differences between individual farms can

Table 4.16 Effect of varying assumptions on GHG emissions

Parameter	Bound	Mean % difference	Range of % difference	Rank Correlation
Using Holos assumptions	N/A	5.72%	-32.0% – 18.7%	0.9869
Low/Medium/High Diet cut-off values	Lower[a]	-0.996%	-3.88 – 0%	0.9998
	Upper[a]	0.71%	0 – 4.61%	0.9998
Fertilizer rates	Lower	-0.75%	-3.68 – 0%	0.9998
	Upper	1.37%	-0.13 – 3.68%	0.9998
Crop yields	Lower	1.45%	0.019 – 5.72%	0.9998
	Upper	-0.78%	-3.82 – -0.012%	0.9999
Manure handling	All solid	-10.30%	-15.00 – -5.48%	0.9996
	All liquid	2.65%	-0.27 – 7.12%	0.9999
Time spent at young heifer stage	Lower	0.59%	0 – 1.94%	1.000
	Upper	-0.38%	-1.26 – 0%	1.000
Time spent at calf stage (lower = 0 weeks, upper = 6 weeks)	Lower	-1.25%	-6.74 – 0.18%	0.9998
	Upper	0.047%	-0.0052 – 0.15%	1.000

[a] Lower and upper bounds are -/+ 20% of the original assumption

be large, particularly for the scenarios where all Holos assumptions are used (i.e., as opposed to the original analysis which uses GHG emissions modified for specific Alberta conditions) and where manure handling practices are varied. As such, production frontiers for the three scenarios are estimated: using all Holos assumptions, assuming only solid manure handling, and assuming only liquid manure handling. The resulting parameters (Table 4.17) and efficiency estimates (Table 4.18) are compared. Overall, the results are very similar, suggesting the estimates are robust to moderate changes in the GHG assumptions.

Table 4.17 Comparison of coefficients from different sensitivity analysis scenarios to the original results

	Original	**All Holos assumptions**	**All solid manure handling**	**All liquid manure handling**
Intercept	-0.0090	0.0085	-0.0364**	0.0030
Forage[3]	0.0116	0.0136	0.0131	0.0104
Concentrate	-0.0241***	-0.0467***	-0.0144	-0.0287***
Labour	-0.0483***	-0.0213*	-0.0574***	-0.0521***
Capital	-0.0251***	-0.0164**	-0.0319***	-0.0249***
Other	-0.0350***	-0.0096	-0.0581***	-0.0338***
Livestock sales	0.0174***	0.0194***	0.0255***	0.0167***
Linear time trend	-0.0062**	-0.0040	-0.0075***	-0.0064**
Quadratic time trend	-0.0002	-0.0001	-0.0002	-0.0002
GHG	-0.3642***	-0.4198***	-0.3359***	-0.3560***
Forage*Forage	0.0024	-0.0080	0.0036	0.0044
Forage*Concentrate	-0.0782***	-0.0304	-0.0768***	-0.0752***
Forage*Labour	0.0057	-0.0284	0.0138	0.0052
Forage*Capital	-0.0100	-0.0160	-0.0062	-0.0097
Forage*Other	0.0413	0.0580**	0.0418	0.0474*
Concentrate*Concentrate	0.0268***	-0.0010	0.0244**	0.0262***
Concentrate*Labour	-0.0330	-0.0105	-0.0296	-0.0324
Concentrate*Capital	-0.0360***	-0.0171*	-0.0399***	-0.0364***
Concentrate*Other	0.0248	0.0360**	0.0291	0.0293
Labour*Labour	0.0045	-0.0064	0.0045	0.0025
Labour*Capital	0.0503***	0.0366***	0.0541***	0.0507***
Labour*Other	-0.0024	-0.0206	-0.0028	-0.0053
Capital*Capital	0.0167*	0.0065	0.0157	0.0153
Capital*Other	-0.0451***	-0.0230	-0.0466***	-0.0434**
Other*Other	0.0586***	0.0098	0.0657***	0.0598***
LivestockSales*LivestockSales	0.0078	0.0063	0.0076	0.0078
GHG*GHG	0.0214	-0.0132	0.0394	0.0313
LivestockSales*GHG	0.0754***	0.0299	0.0717**	0.0717**
LivestockSales*Forage	-0.0030	0.0082	-0.0035	-0.0023
LivestockSales*Concentrate	-0.0137	-0.0089	-0.0141	-0.0135
LivestockSales*Labour	-0.0750***	-0.0467**	-0.0764**	-0.0757**
LivestockSales*Capital	0.0137	0.0103	0.0153	0.0147
LivestockSales*Other	-0.0129	-0.0039	-0.0082	-0.0101

GHG*Forage	0.0306	0.0220	0.0148	0.0180
GHG*Concentrate	0.0809**	0.0350	0.0830**	0.0759**
GHG*Labour	-0.0312	0.0282	-0.0465	-0.0261
GHG*Capital	0.0009	-0.0004	0.0036	0.0029
GHG*Other	-0.1279***	-0.0582	-0.1448***	-0.1401***
Joint inefficiency model				
Intercept	0.5416***	0.6082***	0.5497***	0.5482***
Herd size	0.0001	0.0002**	0.0001	0.0001
Milk yield	-0.0281***	-0.0298***	-0.0282***	-0.0281***
Linear time trend	0.0063	0.0026	0.0058	0.0058
Quadratic time trend	0.0000	0.0002	0.0000	0.0000
Butterfat	-0.0063	-0.0202	-0.0079	-0.0087
Years farming	0.0005	-0.0006*	0.0006	0.0006
Proportion of paid labour	0.0060	-0.0080	0.0048	0.0026
Proportion of purchased feed	0.0072	-0.0024	0.0094	0.0097
Debt to asset ratio	0.0588	-0.2138	0.0976	0.0553
North/South dummy	0.0153**	0.0074	0.0166**	0.0144**
Proportion of forage in diet	-0.1703***	-0.0290	-0.1832***	-0.1644***
σ^2	0.0028***	0.0021***	0.0031***	0.0029**
γ	0.8020***	0.7634***	0.7981***	0.8017**

Table 4.18 Comparison of the efficiencies derived from the different scenarios to the original

Bound	Mean % difference	Range of % difference	Rank Correlation
Holos	0.65%	-6.65 – 10.38%	0.8813
Solid manure	-0.20%	-2.45 – 1.80%	0.9957
Liquid manure	0.30%	-1.12 – 2.32%	0.9978

4.6 Chapter Summary

Stochastic frontier analysis is used to estimate enhanced hyperbolic distance functions with and without considering GHG emissions as a detrimental output. Using an unbalanced panel sample of Alberta dairy producers from 1996-2016, frontiers using a translog functional form are jointly estimated with inefficiency models using maximum likelihood techniques. Two beneficial outputs are considered– milk and livestock. The detrimental output, GHG emissions, is derived from Holos algorithms with Alberta specific assumptions. Input variables are forage, concentrate, labour, capital, and other. The inefficiency model included the variables herd size, milk yield, time, butterfat, years farming, proportion of paid labour, proportion of purchased feed, debt to asset ratio, region, and proportion of forage in the diet.

Environmental efficiency estimates are highly correlated with technical efficiency, suggesting the goal of emission reduction aligns with reaching full technical efficiency. The results from the distance function estimation indicate that mean efficiency levels for Alberta dairy farms (at least for those producers in the sample) are very high; that is, many farms are already close to the frontier. As a result, further reductions in GHG emissions may come at a significant cost. This is evidenced by examining the shadow price results. A reduction in GHG emissions results in a reduction in milk output, thus imposing a private cost on the producers in return for generating a social benefit. This study estimates this cost at over $300 per tonne of reduced emissions, in terms of reduced milk revenue.

The elasticity analysis revealed increasing use of inputs may reduce GHG emissions, with the exception of forage where its increased use will raise total GHG emissions, holding all other inputs and outputs constant. However, reduced use of forage may have detrimental effects on output due to negative animal health effects, such as ruminal acidosis, that can result from insufficient forage levels in the diet

(Gozho et al. 2007). In addition, the inefficiency model suggests that increasing the ratio of forage in the diet can actually improve environmental efficiency. Inefficiency model results also indicate that increased milk yield per cow and being in the Southern region of Alberta can improve environmental efficiency; that is, reduce GHG emissions while maintaining economic viability.

Chapter 5. Data Envelopment Analysis

Chapter Five provides a discussion of the data envelopment analysis (DEA) portion of this study. As mentioned in the previous chapter, a separate analysis using a smaller but more detailed subset of the Dairy Cost Study is performed. Due to the small number of observations in this dataset, it is infeasible to undertake econometric analysis. Therefore, DEA is used to estimate efficiency. The specific objectives for this chapter are to: calculate more accurate GHG emissions using the information collected in the small dataset, derive and compare the resulting technical and environmental efficiencies, estimate the effect of farm and producer characteristics on the efficiencies, and compare the DEA results to those obtained from stochastic frontier analysis.

This chapter begins with a discussion of the DEA model, followed by a summary of the procedure used for the second stage efficiency model. Next, a description of the detailed dataset is provided. The results are then presented, including the efficiency estimates, factors that affect efficiency, and a comparison to SFA results.

5.1 Empirical Model

DEA, as introduced in Chapter Three, is an application of mathematical programming that involves "solving" for a deterministic piece-wise frontier. It has many strengths unique from SFA, which make it an appropriate choice for a complementary analysis for this study. The key advantage of DEA is the ability to estimate efficiency with limited data requirements, enabling the use of a small subset of the Dairy Cost Study that contains detailed information on farming practices. Ideally, SFA would be used for the small dataset, as it allows for a more direct comparison to the results in

Chapter Four. However, the size of the small dataset, at a total of 24 observations, causes econometric analysis to be infeasible, especially as the number of observations is less than the number of parameters in the translog hyperbolic distance function used in SFA. In addition, with small sample sizes, common issues include large standard errors (i.e., low statistical power) and model convergence failures as likelihood functions may exhibit flat areas (Mills and Patterson 2009).

DEA is not without its drawbacks; for example, it does not differentiate between producer inefficiency and stochastic effects, which Chapter Four suggests are significant. In addition, DEA is sensitive to outliers and requires bootstrapping for statistical analysis (Simar and Wilson 2007). However, Ruggiero (1999) found that even if the stochastic model is the correct specification, DEA outperforms SFA when sample sizes are small (i.e., their study used a minimum of 25 observations). Furthermore, with DEA, assumptions are not required regarding functional form or distributional assumptions, avoiding the issue of potential misspecification seen in parametric estimations.

As discussed in Chapter Three, there are many ways to estimate efficiency when a detrimental output is present; for example, through distance functions, the by-production approach, and additive or multiplicative transformations of the bad output. To maintain consistency with the SFA portion of this study and to avoid the highly variable results from different methods of aggregation or transformations, an enhanced hyperbolic distance function approach is used for the DEA portion as well.

The basic DEA model presented in Chapter Three considers input orientated efficiency assuming constant returns to scale (CRS). Building upon that, the enhanced hyperbolic distance function, which considers the ability of the producer to proportionally increase good outputs while decreasing bad outputs and inputs, can be represented:

$$D_H(\boldsymbol{x}', \boldsymbol{y}', \boldsymbol{b}') = \inf\{\theta' \geq 0: \left(\boldsymbol{x}'\theta', \frac{y\prime}{\theta\prime}, \boldsymbol{b}'\theta'\right)\} \quad s.t. \tag{5.1}$$

$$\sum_{i=1}^{I} \lambda_i y_{im} \geq \frac{y\prime_{im}}{\theta\prime},\ m = 1, \ldots, M$$

$$\sum_{i=1}^{I} \lambda_i b_{ir} = b'_{ir}\theta',\ r = 1, \ldots, R$$

$$\sum_{i=1}^{I} \lambda_i x_{in} \leq x'_{in}\theta',\ n = 1, \ldots, N$$

$$\sum_{i=1}^{I} \lambda_i = 1$$

where, assuming I number of producers, θ' represents the efficiency for an individual (denoted by an apostrophe) producer, $\boldsymbol{x}'$ is a *N* x 1 vector of inputs for that producer, $\boldsymbol{y}'$ is a *M* x 1 vector of good outputs, $\boldsymbol{b}'$ is a *R* x 1 vector of bad outputs, and $\boldsymbol{\lambda}$ is a vector of endogenously determined weights. The objective function represents the ability of the producer to radially contract input vector $\boldsymbol{x}'$, contract detrimental output $\boldsymbol{b}'$, and expand the output vector $\boldsymbol{y}'$ as much as possible while remaining in the feasible production set. The left hand side of the equations describes the fully efficient quantity while the right hand side represents the current practice and its radial distance. $\sum_{i=1}^{I} \lambda_i = 1$ is the convexity constraint that allows for variable returns for scale (VRS). VRS is assumed because it allows for more flexibility in regards to returns to scale, especially as the SFA results suggest decreasing returns to scale for the dairy farmers sampled.

When using DEA, a jointly estimated inefficiency model is not feasible. As a result, in order to examine the relationship between efficiency and farm and producer characteristics, a second stage regression is used. Given that maximum efficiency levels cannot exceed one, a Tobit model with the dependent variable truncated from the right at one is estimated:

$$\hat{\theta}_i = z_i\varphi + \varepsilon_i \quad (5.2)$$

where $\hat{\theta}_i$ is the efficiency derived from Expression 5.1, z_{it} is a vector of variables associated with efficiency, and φ is a corresponding vector of coefficients to be estimated. For this study, the Tobit regression is referred to as an efficiency model to distinguish from the joint inefficiency model estimated in Chapter Four, because the dependent variable in this case is efficiency instead of inefficiency. To correct for biases present in a second stage regression, and to allow econometric analysis with DEA results, bootstrapping procedures adapted from Simar and Wilson (2007) are used. The process is detailed below:

1. $\hat{\theta}_i$ is computed by solving Expression 5.1 for all producers
2. Equation 5.2 is estimated to obtain the estimates $\hat{z}_i$ and $\widehat{\sigma_\varepsilon}$
3. For each $i = 1, \ldots, I$, the four steps (3*a.* to 3*d.*) are repeated *L*$_1$ times to obtain I sets of bootstrap estimates $B_i = \{\hat{\theta}^*{}_{ib}\}_{b=1}^{L_1}$

   3a. ${\varepsilon_i}^*$ is drawn from the *N*(0, ${\widehat{\sigma_\varepsilon}}^2$) distribution with left truncation at $(-z_i\hat{\varphi})$ and right truncation at $(1-z_i\hat{\varphi})$

   3b. The Tobit model $\theta_i^* = z_i\hat{\varphi} + {\varepsilon_i}^*$ is estimated to obtain the estimates θ_i^*

   3c. Another dataset (x_i^*, y_i^*, b_i^*) is constructed where $x_i^* = \frac{\hat{\theta}_i}{\theta_i^*}x_i$, $y_i^* = \frac{\theta_i^*}{\hat{\theta}_i}y_i$, $b_i^* = \frac{\hat{\theta}_i}{\theta_i^*}b_i$

   3d. The dataset in *c.* is used to compute $\hat{\theta}^*{}_i$ by solving Expression 5.1

4. For each $i = 1, \ldots, I$, the bias-corrected efficiency $\tilde{\theta}_i = \hat{\theta}_i - Bias(\hat{\theta}_i)$ is calculated where $Bias(\hat{\theta}_i) = \frac{\sum_{b=1}^{L_1}\hat{\theta}^*{}_{ib}}{L_1} - \hat{\theta}_i$

5. Using $\tilde{\theta}_i$, Equation 5.2 is estimated to obtain the estimates $\hat{\hat{\varphi}}$ and $\hat{\hat{\sigma}}_\varepsilon$
6. For each $i = 1, \ldots, I$, steps 6*a.* and 6*b.* are repeated L_2 times to obtain a set of bootstrap estimates $\left\{(\hat{\hat{\varphi}}^*, \hat{\hat{\sigma}}_\varepsilon^*)_b\right\}_{b=1}^{L_2}$

   6a. ${\varepsilon_i}^{**}$ is drawn from the $N(0, {\hat{\hat{\sigma}}_\varepsilon}^2)$ distribution with left truncation at $(-z_i\hat{\hat{\varphi}})$ and right truncation at $(1 - z_i\hat{\hat{\varphi}})$

   6b. The Tobit model $\theta_i^{**} = z_i\hat{\hat{\varphi}}^* + {\varepsilon_i}^{**}$ is estimated to obtain estimates of $\hat{\hat{\varphi}}^*$ and $\hat{\hat{\sigma}}_\varepsilon^*$
7. The confidence intervals for the efficiency model parameters are derived. As $Pr(-b_{\alpha/2}^* \leq \hat{\hat{\varphi}}^* - \hat{\hat{\varphi}} \leq -a_{\alpha/2}^*) \approx 1 - \alpha$, where α is the level of significance, the confidence interval can be constructed: $[\hat{\hat{\varphi}} + a_{\alpha/2}^*, \hat{\hat{\varphi}} + b_{\alpha/2}^*]$. For example, using a five percent level of significance and 2000 bootstrap replications, when all the replications are ranked from smallest to largest, $-b_{\alpha/2}^*$ will be the value of the 50th smallest replication while $-a_{\alpha/2}^*$ is the value of the 50th largest replication.

For this study, a value of 0.05 is used for α, and 2000 replications are used for both L_1 and L_2.

To perform the analysis described above, as Expression 5.1 is non-linear, the DEA program is first linearized following Färe et al. (1989), then evaluated using the R package "lpSolve" (Berkelaar 2015).

5.2 Data and Variables

As discussed in Chapter Four, the Dairy Cost Study does not include several of the parameters required by Holos to calculate GHG emissions. To elicit information about specific housing, feeding, manure, pasture, and cropping practices used by producers, a separate questionnaire is created. A copy of the questionnaire is provided in Appendix K. Target questionnaire respondents are the producers participating in the 2016 Dairy Cost Study, allowing the resulting dataset for the DEA portion of this study to include reported values for detailed farming practices in addition to the information collected through the regular Dairy Cost Study. Alberta Agriculture and Forestry contacted all producers in the 2016 Dairy Cost Study to see if they are willing to fill out an additional detailed questionnaire. Of the 46 producers that participated in the 2016 Dairy Cost Study, 29 producers initially agreed to the additional questionnaire. In total, 24 questionnaire responses are collected; five producers were not able to complete the questionnaire for various reasons.

The variables used in the DEA analysis, and their derivations, are the same as for the SFA analysis in Chapter Four, with the exception of GHG emissions. The information from the detailed dataset is used to calculate GHG emissions, and the GHG assumptions from Chapter Four are only used when the information is not present in the dataset (e.g., proportion of pregnant cows in the herd), or for fields some producers may have left blank (e.g., average weight of different animal categories).

The descriptive statistics for the DEA dataset[8] are presented in Table 5.1. Compared to the large dataset, the average per farm values of all the inputs and outputs are larger for the DEA dataset, except for capital. Average values for herd size, milk yield, butterfat levels, and years farming are also larger, while debt to asset ratio is

[8] The DEA dataset refers to the data collected from the 24 producers who provided detailed supplementary production practice information through the questionnaire.

lower. The proportion of farmers in the North, proportion of purchased feed, and proportion of paid labour are similar between datasets.

5.3 Results

Due to problems with the convergence of the associated efficiency model when the intended model described above is estimated, a variety of DEA models are estimated to find an appropriate specification; for example, output orientated hyperbolic distance functions, GHG as an input, and CRS. Results from the alternative models are presented in Appendix J. Overall, the efficiency model based on an enhanced hyperbolic DEA model assuming VRS, with two variables removed, had the highest statistical significances in terms of the variables, and the results from that model are discussed below. The two omitted variables are livestock output, which is removed from the production frontier as it consists of only 9% of total revenue, and forage ratio, which is omitted from the efficiency model due to high multicollinearity with other efficiency model variables. While the resulting model is not as representative of the true state of dairy enterprises in Alberta and provides less potential conclusions, the trade-offs are relatively small for the convergence of the efficiency model.

5.3.1 Efficiency estimates

Similar to Chapter Four, to examine the impact of considering GHG emissions on the efficiency of dairy farmers, results from enhanced hyperbolic distance functions with and without GHGs as a detrimental output are compared. Efficiency estimated from the

Table 5.1 Descriptive statistics for the DEA dataset (n = 24)

	Name	Mean	Std. Dev.	Min	Max
Positive Outputs	Milk output (hL FPCM[a])	11259.56	1616.47	7919.05	3131.53
	Livestock output[b]	75212.40	18358.33	89937.10	14736.62
Detrimental Output	GHG (kg CO_2 eq)	1441150.92	286634.02	1404214.17	437587.67
Inputs	Forage[b]	161652.27	37015.88	181340.04	56003.15
	Concentrate[b]	255906.36	39994.13	195930.44	54082.25
	Labour (hours)	8086.58	1157.45	5670.30	3849.00
	Capital[c]	1004082.96	512992.43	2513139.38	91402.52
	Other[b]	100890.41	18573.44	90990.89	20717.18
Inefficiency Model Variables	Number of cows	155.99	30.93	151.51	54.33
	Milk yield (L FPCM/day)	20.73	0.67	3.26	12.74
	Butterfat (%)	4.03	0.04	0.19	3.57
	Years farming	27.75	2.84	13.91	1.00
	Paid labor proportion	0.2567	0.0609	0.2983	0.0000
	Purchased feed proportion	0.6464	0.0434	0.2127	0.3186
	Debt to asset ratio	0.0135	0.0036	0.0177	0.0000
	Proportion of forage in diet	0.3868	0.0202	0.0988	0.2173
	Region	North = 11 observations		South = 13 observations	

[a] Fat and protein corrected milk, where milk is standardized to 4% fat and 3.3% milk protein (IDF 2010)
[b] The quantity is the implicit quantity obtained by dividing the value of sales (or expenses) by the implicit price (Fisher Price Index with 1996 as the base year)
[c] The quantity of capital is proxied by the annual cost of capital (see Section 4.2.3.3)

frontier including GHGs is denoted environmental efficiency (EE) and efficiency from the frontier without GHGs as technical efficiency (TE).

The descriptive statistics of the DEA efficiency results are presented in Table 5.2. Overall, efficiency levels are very high, with only five producers not at full efficiency in both models, leading to an average TE of 0.984 and average EE of 0.986. The high average efficiency and large proportion of fully efficient firms for this study can be attributed to the relatively low sample size. In DEA, when there is a low number of individual firms, the proportion of fully efficient firms will often be relatively large, leading to a high average efficiency (Alirezaee et al. 1998). Other dairy efficiency DEA studies also found high (albeit lower than this study's) efficiency levels– Cloutier and Rowley (1993) found an average technical efficiency of 0.913 for Quebec dairy farmers (n = 187), and Wetteman and Latacz-Lohmann (2017) estimated an average technical efficiency of 0.895 for German dairy farms (n = 216). In addition, dairy efficiency studies where a high number of producers are fully efficient are common for DEA; for example, Cloutier and Rowley (1993) found 40 observations out of 187 to have a technical efficiency of one, Stokes et al. (2007) found this for six out of 34 farms, and Fraser and Cordina (1999) had 18 out of 50 producers that are fully efficient.

TE and EE calculated from DEA are also very similar, with a Pearson's correlation coefficient of 0.9543 and a Spearman's correlation coefficient of 0.9931. A high correlation between TE and EE for dairy farms is also present in Shortall and

Table 5.2 DEA efficiency results: Descriptive statistics (n = 24)

Model	Mean	Std. Dev.	Min	Max
With GHG	0.9862	0.0297	0.9018	1
Without GHG	0.9838	0.0350	0.8860	1

Barnes' (2016) DEA study, where Spearman's correlations between 0.92–0.99 are found, with variations depending on how EE is defined (i.e., GHG included as an input, or included as an output using the inverse of GHGs).

5.3.2 Factors affecting efficiency

The efficiency model parameter estimates for TE and EE are presented in Table 5.3. A positive coefficient indicates the variable contributes positively to technical or environmental efficiency. It should be noted that, through the bootstrapping process detailed earlier, there is an implicit bias correction applied when constructing the confidence intervals. However, the actual Tobit parameter estimates are uncorrected for this bias and, as a result, may not fall within the estimated confidence intervals. Between the GHG and no GHG models, the parameter estimates are statistically similar in terms of magnitude, significance, and sign. This is not surprising given the high correlation between TE and EE efficiency estimates.

Increasing herd size, milk yield per cow, butterfat levels, years farming, and debt to asset ratio can potentially improve TE and EE. A positive coefficient for herd size suggests possible scale effects for the producers sampled. A higher milk yield reflects higher productivity, and more experienced farmers may be more efficient. Increasing butterfat levels may indicate improved management ability as quota is measured in

Table 5.3 Bootstrapped[a] Tobit parameter estimates for the efficiency model (α = 0.05)

	No GHG	Confidence Interval		GHG	Confidence Interval	
	Estimate[b]	lower bound	upper bound	Estimate[2]	lower bound	upper bound
Intercept	-1.4172*	-5.0299	-2.2348	-0.8209*	-3.6383	-1.4015
Herd Size	0.0009*	0.0012	0.0022	0.0007*	0.0009	0.0018
Milk Yield	0.0430*	0.0682	0.1024	0.0351*	0.0550	0.0843
Butterfat	0.4187*	0.5199	1.1557	0.3021*	0.3498	0.8695
Years farming	0.0061*	0.0070	0.0174	0.0051*	0.0060	0.0142
Proportion of paid labour	-0.2640*	-0.7510	-0.2807	-0.2179*	-0.6230	-0.2285
Proportion of purchased feed	-0.2636*	-0.8359	-0.1675	-0.1866*	-0.6234	-0.1004
Debt to asset ratio	6.2565*	8.6996	16.9029	4.8084*	6.5122	12.9993
North/South dummy (North = 1)	-0.2883*	-0.6923	-0.4571	-0.2416*	-0.5769	-0.3803

[a] Bootstrapped with 2000 replications following Simar and Wilson (2007)
[b] * denotes significance at the 5% level. As the parameter estimate is uncorrected for bias, it may not fall within the confidence interval.

butterfat. A higher debt to asset ratio can be a signal of farmer optimism, as well as farm expansion, which can reflect higher availability of capital and machinery.

Factors with negative effects on TE and EE are proportion of paid labour, proportion of purchased feed, and being in Northern Alberta. Paid labour and purchased feed may impose additional transaction costs on producers (e.g., hiring labour, feed transportation) and may be of lower quality. Southern Alberta farms may be more efficient due to differences in cropping practices (e.g., higher proportion of corn silage– 18% of Northern Alberta farmers in the DEA dataset planted corn silage compared to 46% of Southern Alberta farms) and environmental factors (e.g., warmer temperature, which can influence factors such as crop yields and cattle maintenance energy).

Overall, the results are mostly consistent with other DEA studies that consider dairy environmental efficiency. For example, Shortall and Barnes's (2016) study also found very similar efficiency model results between TE and EE for Scottish dairy farms. For their study, herd size and milk production per cow were positively correlated with TE and EE, while years farming waws insignificant. In Urdiales et al.'s (2016) study on the environmental efficiency of Spanish dairy farmers, their study found that younger farmers and farmers who plan on continuing their dairy operation in five years had higher EE.

5.3.3 Comparison to stochastic frontiers

The results obtained from DEA are compared to those from SFA. Specifically, the efficiency estimates and the factors that affect efficiency are evaluated. Aside from the correlation between TE and EE, the results cannot be directly compared because efficiencies are measures relative to each frontier. As the frontier for SFA is derived from 1075 observations from 1996-2016 while the DEA sample consists of 24 producers from 2016, the frontiers are likely to be very different. However, comparing the results can still reveal valuable insights such as robustness of the results, as well as the differences between parametric and non-parametric forms of estimation.

For comparison of efficiency estimates, to maintain consistency, only the SFA efficiency estimates from the same 24 producers used for DEA are considered. Similar to DEA, mean efficiencies from SFA are very high, with an average TE of 0.909 and EE of 0.935, respectively. Also aligning with the DEA results are the high correlations between the SFA derived TE and EE, with a Pearson's correlation coefficient of 0.981 and Spearman's correlation coefficient of 0.944 (Table 5.4).

Table 5.4 Correlation coefficients for technical efficiency (TE) and environmental efficiency (EE) estimated from stochastic frontier analysis (SFA) and data envelopment analysis (DEA)

Parameter 1	**Parameter 2**	**Pearson's correlation**	**Spearman's correlation**
DEA TE	DEA EE	0.9543	0.9931
SFA TE	SFA EE	0.9814	0.9435
DEA TE	SFA TE	0.2083	0.2351
DEA EE	SFA EE	0.0836	0.2682

When comparing the efficiencies estimated from parametric versus non-parametric forms, for both TE and EE, the mean values are statistically different ($p < 0.001$). The correlations between SFA and DEA are low, ranging from 0.084–0.268 (Table 5.4). This is likely due to the high proportion of fully efficient farms in the DEA sample. Other studies have also found lower correlations between efficiency estimates obtained from SFA versus DEA. In Mbaga et al.'s (2003) study comparing dairy technical efficiencies derived from translog and DEA models, a Pearson's correlation coefficient of 0.351 and a Spearman's correlation coefficient of 0.583 were found. Cuesta et al. (2009) compared efficiencies estimated from a translog enhanced hyperbolic distance function to their DEA counterparts for U.S. electricity firms, and found the efficiencies were significantly different with a Spearman's correlation coefficient of 0.67. In Fiorentino et al.'s (2006) study on German banks, the authors found a Spearman's correlation coefficient of 0.188 between SFA and DEA measures of efficiency.

For the factors that affect efficiency, the DEA results are compared to the SFA findings in Chapter Four. For comparison, a SFA model with livestock output and forage ratio omitted is also estimated, and the results are almost identical to the original model, with the exception of years farming, which has no effect on TE or EE for the modified model (Appendix L). A potential explanation for the shift from a negative effect of years farming to an insignificant effect on efficiency for the SFA models is that forage ratio and livestock output, both of which are predicted to have positive effects on efficiency, are no longer controlled for in the modified model. Differing from the SFA models, the DEA model predicts years farming to have a positive effect on TE and EE. A possible reason is that years farming may have a non-linear effect on efficiency, where the effect becomes positive as it increases. The mean years farming is 19.9 for the SFA dataset while it is 27.8 for the DEA dataset.

Looking at the other farm and producer characteristics, the only parameter with the same sign and significance for both TE and EE across DEA and SFA is milk yield per cow. Similar results between DEA and SFA for TE are found in butterfat (positive effect) and purchased feed ratio (negative effect). For EE, being in Northern Alberta decreases efficiency for both DEA and SFA. Results statistically significant for DEA but not for SFA are herd size (positive effect), paid labour proportion (negative effect), and debt to asset ratio (positive effect). The different results between SFA and DEA can be attributed to the different datasets used for both, with potential sample selection bias in the DEA dataset, as the 24 producers who completed the detailed questionnaire may have other attributes that distinguish them from the large dataset.

5.4 Chapter Summary

Data envelopment analysis is used to estimate enhanced hyperbolic distance functions with and without considering GHG emissions as a detrimental output. To see the effect of farm and producer characteristics on efficiency, a second stage bootstrapped Tobit model is used. Variables are derived from a detailed questionnaire on farming practices as well as from the Dairy Cost Study. Due to issues with the convergence of the efficiency model, the DEA model discussed in this chapter considers one beneficial output, milk, and one detrimental output, GHG emissions. Input variables are forage, concentrate, labour, capital, and other. The efficiency model includes the variables herd size, milk yield, time, butterfat, years farming, proportion of paid labour, proportion of purchased feed, debt to asset ratio, and region.

Environmental efficiency estimates are highly correlated with technical efficiency, suggesting the goal of emission reduction aligns with reaching full technical efficiency. Mean technical and environmental efficiency levels for the sampled dairy farms are very high, with many farms on the frontier. Between TE and EE, the efficiency model results are almost identical, and suggest that an increase in herd size, milk yield, butterfat, years farming, or debt to asset ratio can have a positive impact on efficiency. On the other hand, increasing the proportion of paid labour, increasing the proportion of purchased feed, or being in Northern Alberta is predicted to have negative effects on efficiency.

Between the SFA and DEA results, efficiency estimates are significantly different with low correlations. Findings consistent between the stochastic and deterministic forms of estimation include: high average TE and EE with many producers close to the frontier, high correlation between TE and EE, positive effect of milk yield on TE and EE, positive effect of butterfat on TE, negative effect of purchased feed proportion on TE, and negative effect of being in Northern Alberta on EE. Inconsistent results are found for the effect of years farming, herd size, paid labour proportion, and debt to asset ratio where DEA predicts a statistically significant effect while SFA suggests no statistical effect.

Chapter 6. Policy Implications and Conclusions

Climate change is becoming an increasingly pressing societal and policy issue, and Canada has committed to reducing GHGs to 30% below 2005 levels by 2030 (AAF 2017b). As part of that commitment, governments have implemented programs intended to encourage adoption of GHG mitigation practices by agricultural producers. An example of this type of policy instrument is the Alberta Agricultural Carbon Offset Program, where farmers implementing GHG mitigation practices can receive carbon offset credits, which can then be sold on the carbon market (AAF 2015d). However, there are many barriers to the adoption of GHG abatement protocols; for instance, high transaction costs and uncertainty over the economics and mitigation potential of emissions reduction (Cooper et al. 2013, Gerber et al. 2010b). This study aims to reduce the uncertainty surrounding the economics of GHG reduction for Alberta dairy farms by investigating the relationship between farm-level efficiency and whole farm GHG emissions.

To assess the impact on GHGs on farm performance indicators, enhanced hyperbolic frontier distance functions with and without considering GHG emissions are estimated using stochastic frontier analysis (SFA) methods. An equivalent analysis is done using a data envelopment analysis (DEA) approach. This chapter begins with a summary of the results– technical properties of the frontier, efficiency estimates, factors that affect efficiency, and shadow prices. Next, a discussion of the main study conclusions and policy implications is presented. Then, limitations to this study are examined. To end, directions for future research and possible extensions to this study are proposed.

6.1 Summary of Results

The dataset used for SFA is much larger than the one for DEA (i.e., 1075 versus 24 observations). As a consequence, the ability to generalize the SFA results to the entire Alberta dairy sector is greater. As well, more reliability can be placed in the SFA results. In addition, the SFA estimation revealed the stochastic effects to be statistically significant, suggesting that a deterministic form of analysis (e.g., DEA) may be less appropriate. As such, the SFA results are the primary results for this study, and are summarized first. DEA is used as a complementary analysis, and the results are outlined following the SFA summary.

The frontier parameter estimates show the expected signs for the no GHG model; however, forage is not significant for the GHG model, suggesting that when a certain level of GHGs are to be maintained, increasing forage input does not result in an increase in livestock or milk production, holding all other inputs and outputs constant. The magnitudes of the frontier coefficients are small, and similar to previous dairy efficiency studies (e.g., Mbaga et al. 2003), this study found decreasing returns to scale for milk production. In the case of the production elasticities for the detrimental output, all inputs are statistically significant. GHG production elasticities for concentrate, capital, labour, and other, are negative, while it is positive for the forage input.

For both technical and environmental efficiency, average levels for the sampled Alberta dairy farms are very high, with many producers close to the frontier. Similar to other studies (Reinhard et al. 1999, Shortall and Barnes 2013), the linear and rank correlations between technical efficiency (TE) and environmental efficiency (EE) are also very high, suggesting that minimizing GHG emissions aligns with the goal of maximizing beneficial outputs while minimizing inputs for Alberta dairy farmers.

When examining farm and producer characteristics that affect efficiency, the directions of the effects (i.e., the signs of the estimated coefficients) are the same across EE and TE models. However, there are differences between the two inefficiency models in terms of statistical significance. The only variable statistically significant for both TE and EE is milk yield per cow, and the positive relationship between milk yield and efficiency is consistent with past dairy efficiency studies (e.g., Weersink et al. 1990). Differences from other studies are also found (e.g., Cabrera et al. 2010, Mosheim and Lovell 2009, Weersink et al. 1990)– for both TE and EE models in this study, statistically significant effects on efficiency are not found for herd size, proportion of paid labour, and debt-to-asset ratio. Being in Southern Alberta and increasing the proportion of forage in the diet have significantly positive effects (in statistical terms) on environmental efficiency but not technical efficiency. Conversely, variables significant for technical efficiency but not environmental efficiency are butterfat (positive), years farming (negative), and proportion of purchased feed (negative), and these results are similar to the findings from Weersink et al.'s (1990) study on Ontario dairy farmers.

The shadow price, which represents the economic valuation of the marginal rate of transformation between the good outputs and GHGs, is estimated for milk and livestock. This study predicts the opportunity cost of reducing GHG emissions, in terms of foregone milk revenue, to be $308.29 per tonne of CO_2 equivalents. This estimate is consistent with (i.e., within the range of) values of GHG shadow prices predicted by other dairy studies. For livestock, $895.84 of foregone livestock revenue is predicted for every tonne of GHG emissions abated. The large discrepancy in shadow values between the two beneficial outputs (milk and livestock) suggests that Alberta dairy farmers are not allocatively efficient.

The DEA results confirm the key finding of the SFA analysis, which is the high correlation between TE and EE. Further similarities between the two analyses include high average TE and EE with many producers close to the frontier, positive effect of milk yield on TE and EE, positive effect of butterfat on TE, negative effect of purchased feed proportion on TE, and negative effect of being in Northern Alberta on EE. Inconsistent results are found for the effect of years farming, herd size, paid labour proportion, and debt to asset ratio where DEA predicts a statistically significant effect while SFA suggests no statistical effect. The efficiency estimates derived from parametric and non-parametric models also have low correlation values, and this is true for both technical and environmental efficiency. The different datasets used for SFA and DEA are likely the major factor in the differing results.

6.2 Conclusions and Policy Implications

This study focuses on the relationship between technical efficiency and whole farm GHG emissions for Alberta dairy farms. There appears to be no trade-off between reducing GHG emissions and the technical efficiency of dairy farms in Alberta. Environmental efficiency estimates are highly correlated with technical efficiency, suggesting the goal of emission reduction aligns with reaching full technical efficiency. Given that striving for technical efficiency (i.e., maximizing output from a given level of inputs) is consistent with producers' natural objective of profit maximization, this suggests that stringent government interventions (e.g., emission quotas) may not be needed. This is especially true for Alberta dairy farms, where milk production is limited by a quota system. Instead, policies such as education and outreach for topics such as improving farm profitability can be implemented. For industries that are not heavily regulated, and where production is not very homogeneous across farms, there may be a role for additional policy intervention.

While GHG reduction aligns with increasing technical efficiency, when producers are at full efficiency (i.e., at the frontier), there is a steep cost of GHG abatement, where over $300 in milk revenue is predicted to be lost for every tonne of CO_2 equivalent mitigated. Given the high average efficiency for the sample of producers, many Alberta producers will be close to the frontier and so this trade-off would be potentially relevant for much of the population of Alberta dairy farmers. As a private cost is imposed on producers for generating a social benefit, policies where the costs of abatement are shared between government and producers (e.g., subsidies for clean technology) may enhance the adoption of GHG mitigating practices.

The dairy protocols for the Alberta Agricultural Offset Program align with the suggestions above, as the offset protocols focus on practices that can decrease GHGs while encouraging production; for example, increasing milk yield, increasing feed efficiency, retaining fewer heifers, and changing manure management practices (Alberta Environment 2010). Carbon offset programs can also provide similar incentives as a subsidy, where producers are rewarded for their mitigation efforts. In Alberta, farmers received approximately $13/tonne of CO_2 equivalent abated through the offset program (Melchior 2017). However, there has been no offsets generated from the dairy protocols (AAF 2017a). From the results of this study, possible reasons are because many Alberta dairy farmers are already very close to the frontier, where a high cost is involved with GHG abatement, and where further productivity gains may require shifting the frontier through technological improvements, which may also be costly. In addition, there are high transaction costs associated with the Alberta Agricultural Offset Program; for example, keeping records for baseline emissions for three years before mitigation projects can begin (Alberta Environment 2010). When all the costs are considered, the return from selling carbon offset credits may be insufficient to justify participation in the program. To encourage adoption of GHG mitigation practices, further cost sharing from government may be required.

Another contributing factor to the low adoption of productivity protocols may be the structure of Canada's dairy system. Efficiency is measured relative to each frontier, and for this study, the sampled producers are fairly homogenous with a large proportion close to the frontier, where GHG abatement is costly. The high average efficiency of dairy farming is attributed to stability of supply management (Mbaga et al. 2003), and suggests that many producers are on the same level technologically. With high average efficiency, reduction of GHGs without an economic trade-off may require shifting the frontier through technical change. However, supply management reduces competition, and may limit the incentive for innovation or to become more productive (Findlay 2012). The results of Ntoni's (2015) study suggest the cost of production pricing formula used by the Canadian Dairy Commission rewards the adoption of cost minimizing technologies (e.g., milk recording) over productivity enhancing technologies (e.g., genotyping), even if the productivity enhancing technologies significantly enhance farm performance. As the market incentive for adopting new technology may be limited, measures such as facilitating greater competition or subsidizing new technology can potentially improve adoption rates.

The inefficiency model reveals areas where GHGs can be reduced in an economically viable manner. Three farm characteristics that have a significant effect on environmental efficiency, or the ability to reduce GHGs while increasing beneficial outputs and decreasing input use, are milk yield per cow, regional differences, and proportion of forage in the diet. Increasing milk yield, or the productivity, of the cow, can improve environmental efficiency. However, management strategies to achieve increased milk yield independently of changes to factors modeled in the analysis (i.e., input levels) likely require longer-term investments in genetics. Being in the Southern region of Alberta is also associated with higher environmental efficiency. While modifying physical location is not a feasible abatement strategy, there are many differences between Northern and Southern Alberta dairy farms that can potentially be transferable between regions; for example, higher proportion of corn silage, warmer barn temperatures, and different tillage practices. Further study is warranted to pinpoint the specific factors behind the higher EE of Southern Alberta farms, as well as their feasibility for Northern Alberta farms. Lastly, increasing the proportion of forage in the diet, while keeping factors such as milk yield per cow constant, is another area for economically viable GHG abatement. This may be due to the lower cropping energy use (e.g., for tillage, fertilizer production) or the potential animal health benefits (e.g., reduced incidence of ruminal acidosis). Therefore, potential avenues of GHG abatement can be through genetic improvement, increased cropping efficiency, and improving the forage utilization efficiency of dairy cows.

The elasticity analysis further reveals potential areas of GHG mitigation for Alberta dairy farmers. Increasing the inputs: concentrate, labour, capital, and other can decrease GHGs while keeping the levels of other inputs and beneficial outputs constant. While the inefficiency model suggests that a higher proportion of forage in the diet is associated with increased environmental efficiency, the elasticity analysis shows that, holding all other outputs and inputs constant, increasing concentrate input or decreasing forage input can decrease GHG emissions. One reason for these seemingly contradictory results is that the inefficiency model holds many additional factors constant; for example, proportion of purchased feed, proportion of paid labour, milk yield per cow, regional differences, and butterfat levels. In addition, environmental efficiency considers the ability of the producer to reduce GHGs and inputs while increasing beneficial outputs, while the elasticity analysis considers the effect of changing the level of an input on a specific output, and may not translate to increased efficiency. The conclusion may be to increase forage ratio in the diet without large increases in the total amount of forage fed; for example, through processing techniques to increase the digestibility of forage. Lastly, similar to the shadow price result, the lower production elasticities for the GHG models suggests that maintaining a certain level of GHGs restricts productivity, and can be a cost to producers.

Aside from differences in statistical significances for the effects of farm and producer characteristics, the key results are mostly robust between SFA and DEA. Both analyses found high correlation between TE and EE, high average TE and EE, and both suggest that increasing milk yield per cow and being in the Southern region of Alberta is associated with a higher ability to reduce GHGs in an economically viable manner. This suggests that the simplifying assumptions used to calculate GHGs for the large dataset can provide reliable results as the higher accuracy in GHG emissions conferred by the detailed dataset does not have a large impact on the conclusions for this study. As such, the extra lengths to obtain detailed information on farming practices may not be necessary.

An additional contribution of this study is the extension of the limited literature in multi-output analysis with a detrimental output, specifically in regards to dairy efficiency and GHGs. The gaps this study addresses are: evaluating technical and environmental efficiencies from both SFA and DEA contexts, the effect of farm and producer characteristics on the efficiencies, and the production elasticities considering GHG emissions. Methodological contributions include the combination of Battese and Coelli's (1995) inefficiency model with an enhanced hyperbolic distance function, and to emphasize the importance of separating the feed input into forage and concentrate variables as there are significant differences in their effect on GHG production.

6.3 Study Limitations

There are limitations in this study due to the study design and the available data. Firstly, as the Dairy Cost Study is used for this study, data on cropping and farm management practices are not available. This information is extraneous to the Dairy Cost Study as its main objective is to account for the costs and returns of dairy farmers in Alberta to provide a benchmark for milk pricing. As such, many simplifying assumptions are used in this study to calculate the GHG emissions; for example, using the same crop yield for farmers in the same ecodistrict. While representative production practices and environmental parameters are used, they are generalized to regions of Alberta or to the entire Alberta, and may not reflect the true variation between individual farms. In addition, information regarding forage quality is not collected, which may affect forage production elasticities and the estimated effect of the proportion of forage in the diet on the efficiencies. This is because forage quality heavily influences animal performance, yet it can be highly variable across farms. For example, improving forage quality, which increases nutrient availability and the rate of passage through the rumen, can reduce enteric methane while increasing milk yield (Eckard et al. 2010).

Secondly, there is a low sample size for the DEA dataset, which can lead to less representative results and a higher probability of sample selection bias. In addition, insufficient data is likely to have led to the inability to estimate the full efficiency model for DEA as well as the high proportion of fully efficient producers. To encourage completion of the detailed questionnaire, a monetary incentive is provided, and a final response rate of 52.2% is obtained. The original target is 50 survey respondents; however, due to the study design, questionnaire respondents are limited to the producers who participate in the 2016 Dairy Cost Study. Of the 46 producers in the 2016 Dairy Cost Study, 29 producers initially agreed to participate, and 24 completed questionnaires are collected in total.

Thirdly, endogeneity is a common issue when estimating production frontiers and distance functions, as the explanatory variables may be potentially correlated with the error term (O'Donnell 2014). This can lead to biased and inconsistent estimates of the parameters of the production frontier. A possible solution is to use instrumental variables; however, the estimates are sensitive to the instrument chosen and the finite sample properties of the estimator are unknown (O'Donnell 2014). In addition, typical instruments are to use the lagged endogenous variables; however, due to the unbalanced panel nature of the dataset, many observations are not present for consecutive years. Another solution to endogeneity is to use systems of equations estimated with Bayesian methods (Atkinson and Tsionas 2016). However, with detrimental outputs, the price of undesirable outputs are unobservable, leading to difficulty in constructing a system of profit-maximizing first order conditions. As the methods to address endogeneity are not reliably applicable to the dataset used in this study, potential endogeneity is not corrected for in this study.

Fourthly, to avoid problems with convergence, the large dataset is modified. For example, the large dataset is normalized by its geometric mean. As such, only elasticities at the mean of the data can be estimated, rather than at the frontier or for individual producers. In addition, livestock capital is aggregated with total capital, even though their effects on GHG emissions are hypothesized to be different. These modifications of the data limit the conclusions that can be drawn from the results. However, with the available dataset, the modifications are necessary to the convergence of the model.

6.4 Future Research

There are many areas where further research can improve the understanding of the impact of reducing GHG emissions on the economic viability of dairy farms in

Alberta. For example, if detailed data on farming practices are available (e.g., on individual manure management practices), the impact of mitigation strategies, particularly ones specific to the dairy protocols for the Alberta Agricultural Offset Program, on the technical and environmental efficiency of dairy farms can be examined. This study evaluated relatively broader effects; for example, general producer and farm characteristics on efficiency, as well as production elasticities of inputs. As such, conclusions on specific abatement strategies or technologies on the economic viability of dairy farms cannot be made from this study.

Further study can explore alternative methods of estimating efficiency. Multi-output analysis considering a detrimental output is a relatively new field, and alternative estimations can provide methodological insights, as well as test the robustness of the results. For example, for an improved comparison between DEA and SFA techniques, DEA for the large dataset can be performed. In addition, directional distance functions can be estimated, and the results compared to hyperbolic distance functions. For further research, following Vardanyan and Noh (2006), different direction vectors can be specified to see the impact of mapping rules on the shape of the dairy production frontier.

Additionally, environmental efficiency considering different objectives can be estimated. A set definition for environmental efficiency has not been established. This study considered environmental efficiency as the ability of the producer to reduce GHGs and input use while proportionally increasing beneficial output. Other studies take on various definitions. For example, Wetteman and Latacz-Lohmann (2017), in their study on German dairy farms, defined GHG efficiency as the ability to minimize GHG emissions while maintaining constant levels of beneficial output. In Berre et al.'s (2014) dairy efficiency study, society's objective is defined as keeping good outputs constant while minimizing detrimental outputs, while the farmer's objective is to keep detrimental outputs constant while maximizing beneficial outputs. Shortall and Barnes (2013) also considered a frontier where desirable outputs are maximized with the detrimental output as the only input, and another frontier where the only objective is to minimize GHGs. Different types of efficiency can also be estimated; for example, cost efficiency and allocative efficiency. These measures can provide a more comprehensive indicator of economic viability, as they also consider the prices and the objective of cost minimization.

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Appendices

Appendix A. Relevant Holos Algorithms (Little et al. 2013)

Enteric Methane

$$CH_{4\,enteric} = \#\,cattle * \#\,days * GE * \frac{Y_m}{55.65} * (1 - \frac{AR}{100}) \quad \text{(A.1)}$$

$CH_{4\,enteric}$ = Enteric CH_4 emissions (kg)[9]

GE = Gross energy intake (MJ/head/day) (Equation A.2)

Y_m = Methane conversion factor (Table B.2)

55.65 = Energy content of CH_4 (MJ/kg CH_4)

AR = Additive reduction factor, where assuming 2% for lactating cows will have a value of 10

$$GE = \frac{\left[\left(\frac{NE_{maintenance} + NE_{activity} + NE_{lactation} + NE_{prenancy}}{REM}\right) + \left(\frac{NE_{gain}}{REG}\right)\right]}{\frac{TDN}{100}} \quad \text{(A.2)}$$

$NE_{maintenance}$= Net energy of maintenance () (Equation A.3)

$NE_{activity}$ = Net energy of activity () (Equation A.4)

$NE_{lactation}$ = Net energy of lactation () (Equation A.5)

$NE_{prenancy}$ = Net energy of pregnancy () (Equation A.6)

NE_{gain} = Net energy of gain () (Equation A.7)

REM = Ratio of $NE_{maintenance}$ to digestible energy consumed (Equation A.8)

REG = Ratio of NE_{gain} to digestible energy consumed (Equation A.9)

TDN = Percent total digestible nutrients in feed (Table B.2)

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[9] Holos assumes calves do not produce enteric methane

$$NE_{maintenance} = C_f * \ average\ weight^{0.75} \tag{A.3}$$

C_f= maintenance coefficient (Table B.3)

$average\ weight$ = Average of the initial and final weight for that animal group (kg/head)

$$NE_{activity} = C_a * \ NE_{maintenance} \tag{A.4}$$

C_a = Activity coefficient (Holos uses a value of 0 for barns and drylots, and 0.17 for grazing less than 3km/day)

$$NE_{lactation} = milk\ production * \ (1.47 + 0.40 * butterfat) \tag{A.5}$$

$milk\ production$ = Milk production in kg/head/day

$butterfat$ = Percent fat content of milk

$$NE_{pregnancy} = 0.10 * \ NE_{maintenance} \tag{A.6}$$

$$NE_{gain} = 22.02 * ADG^{1.097} * \left(\frac{average\ weight}{C_d * \ mature\ weight}\right)^{0.75} \tag{A.7}$$

ADG = Average daily gain (kg/head/day)

$mature\ weight$ = Weight of the adult animal (kg)

C_d = Gain coefficient (Holos uses a value of 0.8)

$$REM = \ 1.123 - (4.092 * 10^{-3} * TDN) + (1.126 * 10^{-5} * TDN^2) - \frac{25.4}{TDN} \tag{A.8}$$

$$REG = 1.164 - (5.160 * 10^{-3} * TDN) + (1.308 * 10^{-5} * TDN^2) - \frac{37.4}{TDN} \quad \text{(A.9)}$$

Manure Methane

For solid storage and pasture systems, Equation A.10 is used, while Equation A.12 is used for liquid storage systems

$$CH_{4\,manure} = \#\,cattle * \#\,days * VS * 0.161 * MCF \quad \text{(A.10)}$$

$CH_{4\,manure}$ = Manure CH_4 emissions (kg)

VS = Volatile solids (kg/head/day) (For calves, Holos assumes 1.42 kg/head/day, for other animal groups, Equation A.11 is used)

MCF = Methane conversion factor (for pasture, MCF = 0.010, for solid storage, MCF = 0.020, for liquid storage, see Equation A.12)

$$VS = [(GE * (1 - TDN) + (0.04 * GE))] * 0.0499 \quad \text{(A.11)}$$

$$CH_{4\,manure} = \sum_{start\ month}^{end\ month} CH_{4\,manure\_month} * 0.60 \quad \text{(A.12)}$$

$CH_{4\,manure\_month}$= Manure CH_4 emissions for a certain month (kg/month) (Equation A.13)

0.60 = Accounts for the 40% reduction in CH_4 for natural crust covered systems

$$CH_{4\,manure\_month} = VS_{consumed} * 0.161 \quad \text{(A.13)}$$

$VS_{consumed}$ = Monthly volatile solids consumed (kg) (Equation A.14)

$$VS_{consumed} = VS_{available} * f \tag{A.14}$$

$VS_{available}$ = Monthly volatile solids available for conversion to CH4 (kg) (Equation A.15)

f = climate factor (Equation A.17)

$$VS_{available} = VS_{loaded\_month} + (VS_{available\_month-1} - VS_{consumed\_month-1}) \tag{A.15}$$

VS_{loaded_month} = Monthly volatile solids loaded into system for this month (kg) (Equation A.16)

$VS_{available\_month-1}$ = Monthly volatile solids available the previous month (kg) (equivalent to zero for months where liquid manure is emptied)

$VS_{consumed\_month-1}$ = Monthly volatile solids consumed the previous month (kg) (equivalent to zero for months where liquid manure is emptied)

$$VS_{loaded} = VS * \#cattle * \#days * MDP \tag{A.16}$$

MDP = Management and design practice factor (default = 0.45)

$$f = exp\left[\frac{E(T_2 - T_1)}{RT_1T_2}\right] \tag{A.17}$$

E = Activation energy constant (15175 cal/mol)

R = Ideal gas constant (1987 cal*K/mol)

T_1 = 303.16 Kelvin

T_2 = air temperature (Kelvin) (Table B.4)

Manure Nitrous Oxide

$$N_2O_{manure} = (N_2O\ N_{manure\_direct\,rate} + N_2O\ N_{manure\_indirect\,rate}) * \#\,cattle * \#days * 1.57 \quad \text{(A.18)}$$

N_2O_{manure} = Manure N_2O emissions from manure (kg)

$N_2O\ N_{manure\_direct\,rate}$ = Manure direct N_2O-N emission rate (kg/head/day) (Equation A.19)

$N_2O\ N_{manure\_indirect\,rate}$ = Manure direct N_2O-N emission rate (kg/head/day) (Equation A.25)

$$N_2O\ N_{direct\,rate} = N_{excretion\,rate} * EF_{direct} \quad \text{(A.19)}$$

$N_{excretion\,rate}$ = N excretion rate (kg/head/day) (Holos assumes a value of 0.057 for calves. For other animal groups, Equation A.20 is used)

EF_{direct} = Emission factor (kg N_2O-N/kg N) (Table B.5)

$$N_{excretion\,rate} = \frac{PI}{6.25} - \left(\frac{PR_{fetal}}{6.25} + \frac{PR_{lactation}}{6.38} + \frac{PR_{gain}}{6.25}\right) \quad \text{(A.20)}$$

PI = Protein intake (kg/head/day) (Equation A.21)

PR_{fetal} = Protein retained for pregnancy (prorated over the year) (kg/head/day) (Holos assumes 0.0137)

$PR_{lactation}$ = Protein retained for lactation (kg/head/day) (Equation A.22)

PR_{gain} = Protein retained for gain (kg/head/day) (Equation A.23)

6.25 = Conversion from dietary protein to dietary N

6.38 = Conversion from milk protein to milk N

$$PI = \frac{GE}{18.45} * CP \tag{A.21}$$

CP = Crude protein content of the diet (kg/kg) (Table B.2)

$$PR_{lactation} = milk\ production * milk\ protein \tag{A.22}$$

$milk\ production$ = milk production in kg/head/day

$milk\ protein$ = protein content of milk (kg/kg) (the Holos default of 0.035 is used)

$$PR_{gain} = ADG * \frac{268 - (29.4 * \frac{RE}{ADG})}{1000} \tag{A.23}$$

RE = Retained energy (Mcal/head/day) (Equation A.24)

$$RE = 0.0635 * (average\ weight * 0.891)^{0.75} * (ADG * 0.956)^{1.097} \tag{A.24}$$

$$N_2O_{manure\_indirect\ rate} = N_2O\ N_{vol\ rate} + N_2O\ N_{leaching\ rate} \tag{A.25}$$

$N_2O\ N_{leaching\ rate}$ = Manure leaching N_2O-N emission rate (kg/head/day) (Equation A.26)

$N_2O\ N_{vol\ rate}$ = Manure volatilization N_2O-N emission rate (kg/head/day) (Equation A.27)

$$N_2O\ N_{leaching\ rate} = N_{excretion\ rate} * Frac_{leach} * EF_{leach} \tag{A.26}$$

$Frac_{leach}$ = Leaching fraction (Holos a value of zero for solid and liquid manure systems. For pasture systems, use Table B.6)

EF_{leach} = Emission factor for leaching (kg N_2O-N/kg N) (Holos assumes a value 0.0075)

$$N_2O\ N_{vol\,rate} = N_{excretion\,rate} * Frac_{vol} * EF_{vol} \tag{A.27}$$

$Frac_{vol}$ = Volatilization fraction (Table B.5)

EF_{vol} = Emission factor for volatilization (kg N_2O-N/kg N) (Holos assumes a value 0.01)

Soil Nitrous Oxide

$$\begin{aligned} N_2O_{\ soil} = 1.57 * (&N_2O\ N_{fert} + N_2O\ N_{AGR} + N_2O\ N_{BGR} + N_2O\ N_{landmanure} \\ &+ N_2O\ N_{till} + N_2O\ N_{topo} + N_2O\ N_{fallow} + N_2O\ N_{fertleach} \\ &+ N_2O\ N_{AGRleach} + N_2O\ N_{BGRleach} + N_2O\ N_{landmanureleach} \\ &+ N_2O\ N_{fertvol} + N_2O\ N_{landmanurevol}) \end{aligned} \tag{A.28}$$

$N_2O_{\ soil}$ = N_2O emissions from soil (kg)

$N_2O\ N_{fert}$ = N_2O-N emissions from synthetic fertilizer (kg N_2O-N) (Equation A.30)

$N_2O\ N_{AGR}$ = N_2O-N emissions from above ground residue (kg N_2O-N) (Equation A.31)

$N_2O\ N_{BGR}$ = N_2O-N emissions from below ground residue (kg N_2O-N) (Equation A.32)

$N_2O\ N_{landmanure}$ = N_2O-N emissions from land applied manure (kg N_2O-N) (Equation A.33)

$N_2O\ N_{till}$ = N_2O-N emissions from tillage (kg N_2O-N) (Equation A.34)

$N_2O\ N_{topo}$ = N_2O-N emissions from topography (kg N_2O-N) (Equation A.35)

$N_2O\ N_{fallow}$ = N_2O-N emissions from fallow (kg N_2O-N) (Equation A.36)

$N_2O\ N_{fertleach}$ = N_2O-N emissions from leaching of synthetic fertilizer (kg N_2O-N) (Equation A.37)

$N_2O\ N_{AGRleach}$ = N_2O-N emissions from leaching of above ground residue (kg N_2O-N) (Equation A.38)

$N_2O\ N_{BGRleach}$ = N_2O-N emissions from leaching of below ground residue (kg N_2O-N) (Equation A.39)

$N_2O\ N_{landmanureleach}$ = N_2O-N emissions from leaching of land applied manure (kg N_2O-N) (Equation A.40)

$N_2O\ N_{fertvol}$ = N_2O-N emissions from volatilization of synthetic fertilizer (kg N_2O-N) (Equation A.41)

$N_2O\ N_{landmanurevol}$ = N_2O-N emissions from volatilization of land applied manure (kg N_2O-N) (Equation A.42)

$$N_2O\ N_{fert} = Nfert * area * EF_{eco} \tag{A.29}$$

$Nfert$ = Nitrogen fertilizer rate (kg/ha) (Table B.7)

$area$ = Area nitrogen fertilizer applied to (ha)

EF_{eco} = Ecodistrict emission factor (kg N_2O-N/kg N) (Equation A.43) (Table B.6)

$$N_2O\ N_{AGR} = N_{conc\ AGR} * area * EF_{eco} * (yield - (moisture * yield)) * \frac{AGR\ ratio}{Yield\ ratio} \tag{A.30}$$

$N_{conc\ AGR}$ = Above ground residue nitrogen concentration (kg N/kg) (Table B.7)

$yield$ = Crop yield (kg/ha) (Table 4.1)

$moisture$ = Moisture content of crop yield (w/w) (Table B.7)

$AGR\ ratio$ = Ratio of above ground residue (Table B.7)

$Yield\ ratio$ = Ratio of yield (Table B.7)

$$N_2O\ N_{BGR} = N_{conc\ BGR} * area * EF_{eco} * (yield - (moisture * yield)) * \frac{BGR\ ratio}{Yield\ ratio} * \frac{1}{Stand\ length} \tag{A.31}$$

$N_{conc\ BGR}$ = Below ground residue nitrogen concentration (kg N/kg) (Table B.7)

$BGR\ ratio$ = Ratio of below ground residue (Table B.7)

$Stand\ length$ = Length of perennial stand (year) (Holos uses a value of 5.0 for perennial forages. For annual crops, a value of 1.0 is used.)

$$N_2O\ N_{landmanure} = N_{excretion\ rate} * EF_{eco} * \#cattle * \#days * (1 - (Frac_{vol} + Frac_{leach})) \quad \text{(A.32)}$$

$$N_2O\ N_{till} = (N_2O\ N_{fert} + N_2O\ N_{AGR} + N_2O\ N_{BGR} + N_2O\ N_{landmanure}) * (RF_{till} - 1) \quad \text{(A.33)}$$

RF_{till} = Ratio factor for tillage (Holos uses a value of 1.0 for intensive and 0.8 for reduced and no-till for Alberta)

$$N_2O\ N_{topo} = (N_2O\ N_{fert} + N_2O\ N_{AGR} + N_2O\ N_{BGR} + N_2O\ N_{landmanure}) * \frac{(0.017 - EF_{eco})}{EF_{eco}} * F_{topo} \quad \text{(A.34)}$$

F_{topo} = Fraction of land occupied by lower portions of landscape (Table B.6)

$$N_2O\ N_{fallow} = (N_{stubble} - N_{fallow}) * EF_{eco} \quad \text{(A.35)}$$

$N_{stubble}$ = Nitrogen fertilizer rate for stubble (kg/ha) (Table B.8)

N_{fallow} = Nitrogen fertilizer rate for fallow (kg/ha) (Table B.8)

$$N_2O\ N_{fertleach} = Nfert * area * EF_{leach} * Frac_{leach} \quad \text{(A.36)}$$

$$N_2O\ N_{AGRleach} = N_{conc\ AGR} * area * EF_{leach} * Frac_{leach} * \quad \text{(A.37)}$$

$$(yield - (moisture * yield)) * \frac{AGR\ ratio}{Yield\ ratio}$$

$$N_2O\ N_{BGRleach} = N_{conc\ BGR} * area * EF_{leach} * Frac_{leach} *$$ (A.38)

$$(yield - (moisture * yield)) * \frac{BGR\ ratio}{Yield\ ratio} * \frac{1}{Stand\ length}$$

$$N_2O\ N_{landmanureleach} = N_{excretion\ rate} * EF_{leach} * Frac_{leach} * \#cattle * \#days * (1 - (Frac_{vol} + Frac_{leach}))$$ (A.39)

$$N_2O\ N_{fertvol} = Nfert * area * EF_{vol} * Frac_{soilvol}$$ (A.40)

$Frac_{soilvol}$ = Fraction of nitrogen lost by volatilization from soil (Holos uses a value of 0.1)

$$N_2O\ N_{landmanurevol} = N_{excretion\ rate} * EF_{vol} * Frac_{soilvol} * \#cattle * \#days * (1 - (Frac_{vol} + Frac_{leach}))$$ (A.41)

Energy Carbon Dioxide

Total energy CO_2 emissions are the sum of the CO_2 emissions below (Equations A.42 to A.50)

$$CO_{2\ cropfuel} = cropping\ area * E_{fuel} * diesel\ conversion$$ (A.42)

$CO_{2\ cropfuel}$ = CO_2 emissions from cropping fuel use (kg)

$cropping\ area$ = area of crops (ha) of annual crops and perennial forages

E_{fuel} = energy from fuel use (GJ/ha) (Table B.9)

$diesel\ conversion$ = Conversion of GJ of diesel to kg CO_2 (kg CO_2/GJ) (Holos uses a value of 70)

$$CO_{2\ fallowfuel} = fallow\ area * E_{fuel} * diesel\ conversion \tag{A.43}$$

$CO_{2\ fallowfuel}$ = CO_2 emissions from fuel use on fallow land (kg)

$fallow\ area$ = area of fallow (ha)

$$CO_{2\ cropherbicide} = cropping\ area * E_{herbicide} * herbicide\ conversion \tag{A.44}$$

$CO_{2\ cropherbicide}$ = CO_2 emissions from herbicide production for cropland (kg)

$E_{herbicide}$ = Energy for herbicide production (GJ/ha) (Table B.9)

$herbicide\ conversion$ = Conversion of GJ for herbicide production to kg CO_2 (kg CO_2/GJ) (Holos uses a value of 5.8)

$$CO_{2\ fallowherbicide} = fallow\ area * E_{herbicide} * herbicide\ conversion \tag{A.45}$$

$CO_{2\ fallowherbicide}$ = CO_2 emissions from herbicide production for fallow land (kg)

$$CO_{2\ Nfert} = N\ fert\ applied * cropping\ area * N\ fert\ conversion \tag{A.46}$$

$CO_{2\ Nfert}$ = CO_2 emissions from nitrogen fertilizer production (kg)

$N\ fert\ applied$ = Nitrogen fertilizer applied (kg/ha)

$N\ fert\ conversion$ = Conversion of kg nitrogen fertilizer production to kg CO_2 (kg CO_2/kg N) (Holos uses a value of 3.59)

$$CO_{2\,Pfert} = P\ fert\ applied * cropping\ area * P\ fert\ conversion \tag{A.47}$$

$CO_{2\,Pfert}$ = CO_2 emissions from phosphorous fertilizer production (kg)

$P\ fert\ applied$ = Phosphorous fertilizer applied (kg/ha)

$P\ fert\ conversion$ = Conversion of kg phosphorous fertilizer production to kg CO_2 (kg CO_2/kg P) (Holos uses a value of 3.59)

$$CO_{2\,dairy} = \#\ lactating\ cows * \#days * \frac{DairyCowConversion}{365} * Electricity\ conversion \tag{A.48}$$

$CO_{2\,dairy}$ = CO_2 emissions from dairy operations (kg)

$DairyCowConversion$ = kWh per dairy cow per year for electricity (Holos uses the value 968)

$Electricity\ conversion$ = Conversion of kWh of electricity to kg CO_2 emissions (kg CO_2/kWh) (Table 4.7)

$$CO_{2\,liquid\ manure} = \frac{N_{landmanure\ liquid}}{N_{conc\ liquid}} * spreading\ conversion * diesel\ conversion \tag{A.49}$$

$CO_{2\,liquid\ manure}$ = CO_2 emissions from liquid manure spreading (kg)

$N_{landmanure\ liquid}$ = Total nitrogen from liquid land applied manure (kg N)

$N_{conc\ liquid}$ = Nitrogen concentration of liquid manure (kg N/kL) (Holos uses a value of 3.4 for dairy operations)

$spreading\ conversion$ = GJ of energy per kiloliter of liquid manure applied (GJ/kL) (Holos uses a value of 0.0248)

$$CO_{2\ solid\ manure} = \frac{N_{landmanure\ solid}}{N_{conc\ solid}} spreading\ conversion * diesel\ conversion \quad \text{(A.50)}$$

$CO_{2\ solid\ manure}$ = CO_2 emissions from solid manure spreading (kg)

$N_{landmanure\ solid}$ = Total nitrogen from solid land applied manure (kg N)

$N_{conc\ solid}$ = Nitrogen concentration of solid manure (kg N/kL) (Holos uses a value of 5.0 for dairy operations)

Appendix B: Relevant Holos Default Values (Little et al. 2013)

Table B.1 Dairy cattle weights

Cattle group	Weight
Lactating cow	650 kg
Dry cow	650 kg
Bull	1200 kg
Newborn calf	40 kg

Table B.2 Diet coefficients

Cattle group	Diet category	TDN (%)	CP(kg/kg)	Y_m
Lactating cow	High	76	0.18	0.058
	Medium	71	0.17	0.060
	Low	66	0.16	0.065
Dry cow	Close up	63	0.14	0.065
	Far off	54	0.12	0.065
Heifers, bulls	Medium	68	0.18	0.065
	Low	63	0.14	0.065

Table B.3 Maintenance energy coefficients

Cattle group	Maintenance coefficient (C_f)
Lactating cow	0.386
Dry cows and heifers	0.322
Bulls	0.37

Table B.4 Alberta average temperatures (Celsius)

Month	Average temperature
January	-11.4
February	-8
March	-3.1
April	4.5
May	10.7
June	14.8
July	16.9
August	16.1
September	11
October	5.8
November	-3.7
December	-9.7

Table B.5 Manure parameters

Handling system	EF_{direct}	$Frac_{vol}$
Pasture	0.02	0.20
Solid storage	0.005	0.30
Liquid storage	0.005	0.40

Table B.6 Ecodistrict parameters

Ecodistrict	EF_{eco}	$Frac_{leach}$	Soil texture	Soil type	Topography
600	0.0092	0.1815	Brown	Coarse	0
623	0.0115	0.2153	Black/gray	Medium	4.88
681	0.0107	0.2037	Brown	Medium	0
683	0.0103	0.198	Black/gray	Coarse	4.83
684	0.0109	0.2073	Black/gray	Medium	9.07
687	0.0077	0.1591	Black/gray	Medium	1.76
692	0.0107	0.2036	Black/gray	Fine	4.57
703	0.0108	0.2058	Black/gray	Medium	14.34
708	0.0103	0.1982	Black/gray	Medium	13.5
727	0.0103	0.1977	Black/gray	Fine	0.04
728	0.0082	0.1679	Black/gray	Medium	5.8
730	0.0075	0.1565	Black/gray	Medium	12.89
731	0.0094	0.1855	Brown	Medium	13.56
737	0.0095	0.1863	Black/gray	Medium	11.3
738	0.0076	0.158	Black/gray	Medium	14.15
740	0.0092	0.1823	Black/gray	Medium	17.65
744	0.0086	0.1738	Black/gray	Medium	13.55
746	0.0095	0.1857	Black/gray	Medium	15.79
750	0.0074	0.1553	Black/gray	Medium	16.02
769	0.0066	0.1434	Brown	Medium	15
781	0.0061	0.1366	Dark brown	fine	14.55
788	0.0045	0.112	Dark brown	Medium	12.09
790	0.0044	0.1106	Dark brown	Medium	14.71
793	0.0045	0.113	Dark brown	Medium	14.03
797	0.0048	0.1175	Dark brown	Medium	20.75
798	0.0067	0.1448	Black/gray	Medium	14.86
800	0.0063	0.1392	Black/gray	Medium	16.17
801	0.0086	0.1729	Black/gray	Medium	15.06
812	0.0034	0.0959	Brown	Coarse	16.65
815	0.0028	0.0867	Brown	Coarse	8.92
828	0.0038	0.1017	Brown	Medium	11.16

Table B.7 Alberta cropping parameters

	Nitrogen fertilizer rate (kg/ha)			Crop details			Dry matter allocation		
Crop	**Brown soil**	**Dark brown soil**	**Black soil**	**Moisture (w/w)**	**AGR N conc**	**BGR N conc**	**Yield ratio**	**AGR ratio**	**BGR ratio**
Barley	47	42	61	0.12	0.007	0.01	0.38	0.47	0.15
Alfalfa	0	5	5	0.13	0.015	0.015	0.40	0.10	0.50
Hay	0	42	50	0.13	0.015	0.015	0.40	0.10	0.50
Mixed grains	59	56	75	0.12	0.0063	0.01	0.33	0.47	0.20
Oats	59	56	75	0.12	0.006	0.01	0.33	0.47	0.20
Spring wheat	51	47	61	0.12	0.006	0.01	0.34	0.51	0.15

Table B.8 Nitrogen application rates for stubble and fallow (kg/ha)

Soil type	$N_{stubble}$	N_{fallow}
Brown	31	17
Dark brown	47	14
Black	61	21

Table B.9 Energy requirement for cropping systems in Alberta

Soil type	Tillage system	Crop type	E_{fuel} (GJ /ha)	$E_{herbicide}$ (GJ/ha)
Brown	Intensive	Crop	2.02	0.16
		Fallow	1.62	0
	Reduced	Crop	1.78	0.23
		Fallow	1.16	0.07
	No-till	Crop	1.42	0.46
		Fallow	0.34	0.78
Dark brown	Intensive	Crop	2.02	0.16
		Fallow	1.62	0
	Reduced	Crop	1.78	0.23
		Fallow	1.16	0.07
	No-till	Crop	1.42	0.46
		Fallow	0.34	0.78
Black	Intensive	Crop	2.63	0.16
		Fallow	2.35	0.06
	Reduced	Crop	2.39	0.23
		Fallow	1.71	0.11
	No-till	Crop	1.43	0.46
		Fallow	0.93	0.6

Appendix C: Comparison of Holos Results to the Microsoft Excel Version

Table C.1 Comparison of GHG estimates calculated using Holos and the Excel spreadsheet

		Soil emissions (kg N_2O)	Enteric CH_4 (kg CH_4)	Manure CH_4 (kg CH_4)	Manure N_2O (kg N_2O)	Energy CO_2 (kg CO_2)	Total emissions (kg CO_2 eq)
Year 2014 ID 2277	Excel	519.27	27,040.09	5,727.63	408.91	171,971.62	1335434.962
	Holos	516.59	27062.38	5744.78	408.99	169073.98	1332953.16
	% difference	-0.52	0.08	0.30	0.02	-1.71	-0.19
Year 2014 ID 1077	Excel	155.68	6,142.39	1,280.12	97.17	41,572.18	316,406.92
	Holos	163.24	6148.27	1280.81	97.21	43757.87	320,791.36
	% difference	4.63	0.10	0.05	0.04	4.99	1.37
Year 2014 ID 1031	Excel	355.04	12,797.70	2,669.25	196.69	91,846.16	671,128.56
	Holos	350.61	12812.66	2678.66	196.81	91552.49	670375.75
	% difference	-1.26	0.12	0.35	0.06	-0.32	-0.11
Year 2014 ID 1244	Excel	637.05	22,558.30	4,631.63	381.69	192,880.24	1,224,164.96
	Holos	633.61	22,574.46	4,631.63	381.66	190,777.25	1,221,594.27
	% difference	-0.54	0.07	0.00	-0.01	-1.10	-0.21
Year 2014 ID 2179	Excel	314.91	11,983.95	2,676.79	161.82	86,084.45	622,916.49
	Holos	317.89	11,995.61	2,683.93	161.85	87,311.19	625,469.41
	% difference	0.94	0.10	0.27	0.02	1.41	0.41
Year 2014 ID 1251	Excel	289.71	9,652.47	2,211.73	153.71	78,504.35	528,209.06
	Holos	292.51	9,662.86	2,218.04	153.76	79,187.79	530,114.54
	% difference	0.96	0.11	0.28	0.03	0.86	0.36
Year 2014 ID 2201	Excel	543.84	19,178.78	4,358.42	293.16	149,503.67	1,030,349.08
	Holos	547.1	19,201.04	4,371.79	293.31	149,326.41	1,032,074.30
	% difference	0.60	0.12	0.31	0.05	-0.12	0.17
Year 2014 ID 2278	Excel	299.23	22,383.64	5,565.90	356.49	190,517.91	1,146,871.69
	Holos	296.56	22,408.69	5,594.74	356.63	187,787.91	1,144,979.30
	% difference	-0.90	0.11	0.52	0.04	-1.45	-0.17
Year 2014 ID 2272	Excel	368.52	11,266.00	2116.419	186.95	103,829.84	625,738.17
	Holos	370.24	11,279.50	2,122.77	187.03	104,059.92	627,000.03
	% difference	0.46	0.12	0.30	0.04	0.22	0.20
Year 2014 ID 2255	Excel	453.58	16,950.88	2835.344	268.61	145,089.13	890,485.56
	Holos	454.17	16,970.62	2,845.23	268.73	144,235.49	890,647.79
	% difference	0.13	0.12	0.35	0.04	-0.59	0.02
Year 2014 ID 2292	Excel	520.16	16,962.50	3459.213	274.08	170,283.03	952,565.42
	Holos	520.5	16,979.95	3,468.89	274.13	170,056.92	953,201.39
	% difference	0.07	0.10	0.28	0.02	-0.13	0.07
Year 2014 ID 2016	Excel	660.08	36,843.48	7113.314	599.27	245,351.86	1,809,869.31
	Holos	671.79	36,933.53	7,187.96	600.73	245,327.23	1,817,946.75
	% difference	1.74	0.24	1.04	0.24	-0.01	0.44

Year 1998 ID 1050	Excel	356.37	10,254.16	1694.69	167.79	82,688.90	556,158.73
	Holos	359.8	10,261.88	1,698.88	167.79	84,886.27	559,598.90
	% difference	0.95	0.08	0.25	0.00	2.59	0.61
Year 1998 ID 1125	Excel	806.78	23,674.83	6566.67	384.66	247,362.51	1,409,855.99
	Holos	809.79	23,706.59	6,619.24	384.83	248,515.98	1,414,213.52
	% difference	0.37	0.13	0.79	0.04	0.46	0.31
Year 1998 ID 2011	Excel	269.02	10,048.32	2264.916	133.38	86,865.23	538,269.88
	Holos	275.35	10,059.38	2,271.80	133.46	89,979.00	543,586.69
	% difference	2.30	0.11	0.30	0.06	3.46	0.98
Year 1998 ID 2004	Excel	484.89	22,368.53	4388.28	385.81	206,259.89	1,186,187.21
	Holos	476.39	22,300.52	4,420.26	384.39	203,434.56	1,179,723.10
	% difference	-1.78	-0.30	0.72	-0.37	-1.39	-0.55
Year 1998 ID 2128	Excel	369.68	17,453.27	3545.368	290.83	172,879.54	935,878.43
	Holos	363.66	17,476.62	3,556.50	291.01	170,541.32	932,956.23
	% difference	-1.66	0.13	0.31	0.06	-1.37	-0.31
Year 1998 ID 2043	Excel	316.97	9,045.03	1900.336	140.89	88,384.44	516,186.57
	Holos	323.52	9,053.28	1,905.45	140.92	92,348.79	522,269.83
	% difference	2.03	0.09	0.27	0.02	4.29	1.16
Year 2001 ID 2142	Excel	567.31	22,103.50	5580.513	301.62	199,592.49	1,205,010.95
	Holos	564.2	22,119.47	5,615.58	301.64	198,847.88	1,204,876.88
	% difference	-0.55	0.07	0.62	0.01	-0.37	-0.01
Year 2004 ID 1003	Excel	290.69	10,197.77	2219.191	165.55	93,968.28	562,548.39
	Holos	291	10,225.23	2,227.05	165.91	91,052.63	560,797.62
	% difference	0.10	0.27	0.35	0.22	-3.20	-0.31

Appendix D: Alberta Ecodistrict Map

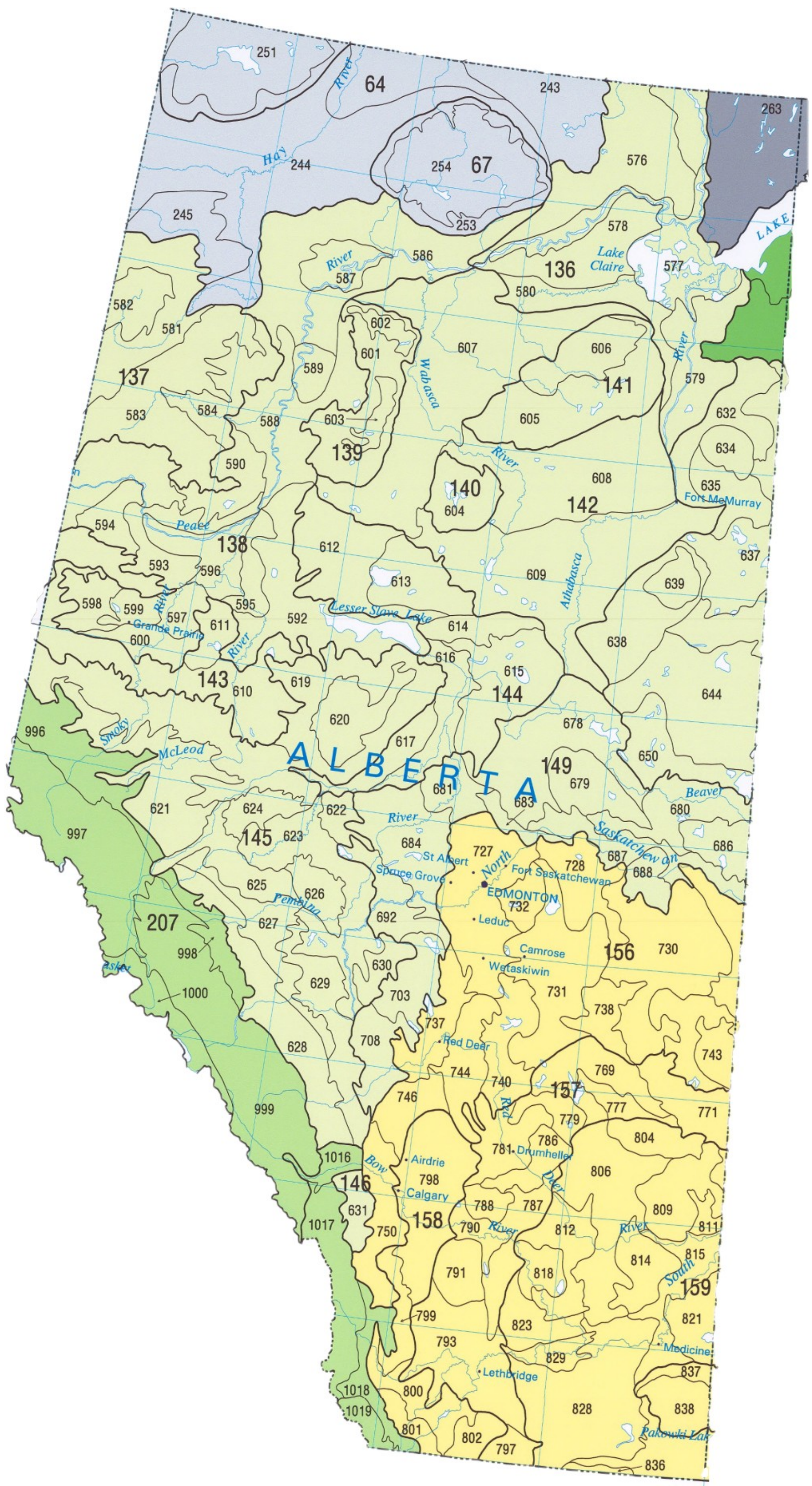


Figure D.1 Map of ecodistricts in Alberta (AAFC 2013)

Appendix E: Assignment of Ecodistrict to County

Table E.1 Assignment of counties in Alberta to the nearest ecodistrict (ecodistrict map presented in Appendix D)

County	Assigned Ecodistrict
Alhambra	708
Barrhead	684
Bashaw	740
Beaver County	731
Blackfalds	737
Bowden	746
Brant	798
Breton	692
Bruderheim	727
Busby	727
Calmar	727
Camrose	731
Carbon	781
Carmangay	793
Carseland	790
Cayley	798
Claresholm	793
Clive	744
Coaldale	793
Coalhurst	793
Cochrane	750
Cranford	828
Crooked Creek	600
Crossfield	798
Delburne	744
Diamond City	793
Didsbury	746
Drayton Valley	623
Duffield	684
Edmonton	727
Etzikom	828
Falun	737
Ferintosh	740
Foremost	828
Ft. Macleod	793
Ft. Saskatchewan	727

Gibbons	727
Hay Lakes	727
Hussar	788
Huxley	781
Innisfail	737
Innisfree	730
Iron Springs	793
James River Bridge	708
Killam	738
Lacombe	737
Leduc	727
Legal	727
Lethbridge	793
Magrath	793
Medicine Hat	815
Milk River	797
Millet	727
Millicent	812
Minburn	730
Monarch	793
Morinville	727
Mountainview	801
Neerlandia	681
New Norway	731
New Sarepta	727
Nobleford	793
Olds	746
Peers	623
Picture Butte	793
Pincher Creek	800
Pine Lake	744
Ponoka	737
Raymond	793
Red deer	737
Redwater	683
Rimbey	703
Rocky Mtn. House	708
Rollyview	727
Sherwood Park	727
St. Paul	687

Stettler	731
Stony Plain	684
Sundre	708
Sylvan Lake	737
Thorsby	684
Three Hills	781
Tofield	731
Two Hills	728
Vermilion	730
Veteran	769
Viking	731
Wainwright	730
Warburg	692
Warner	828
Westlock	681
Wetaskiwin	727
Wildwood	692
Yellowhead County	623

Appendix F: Agricultural Region Map

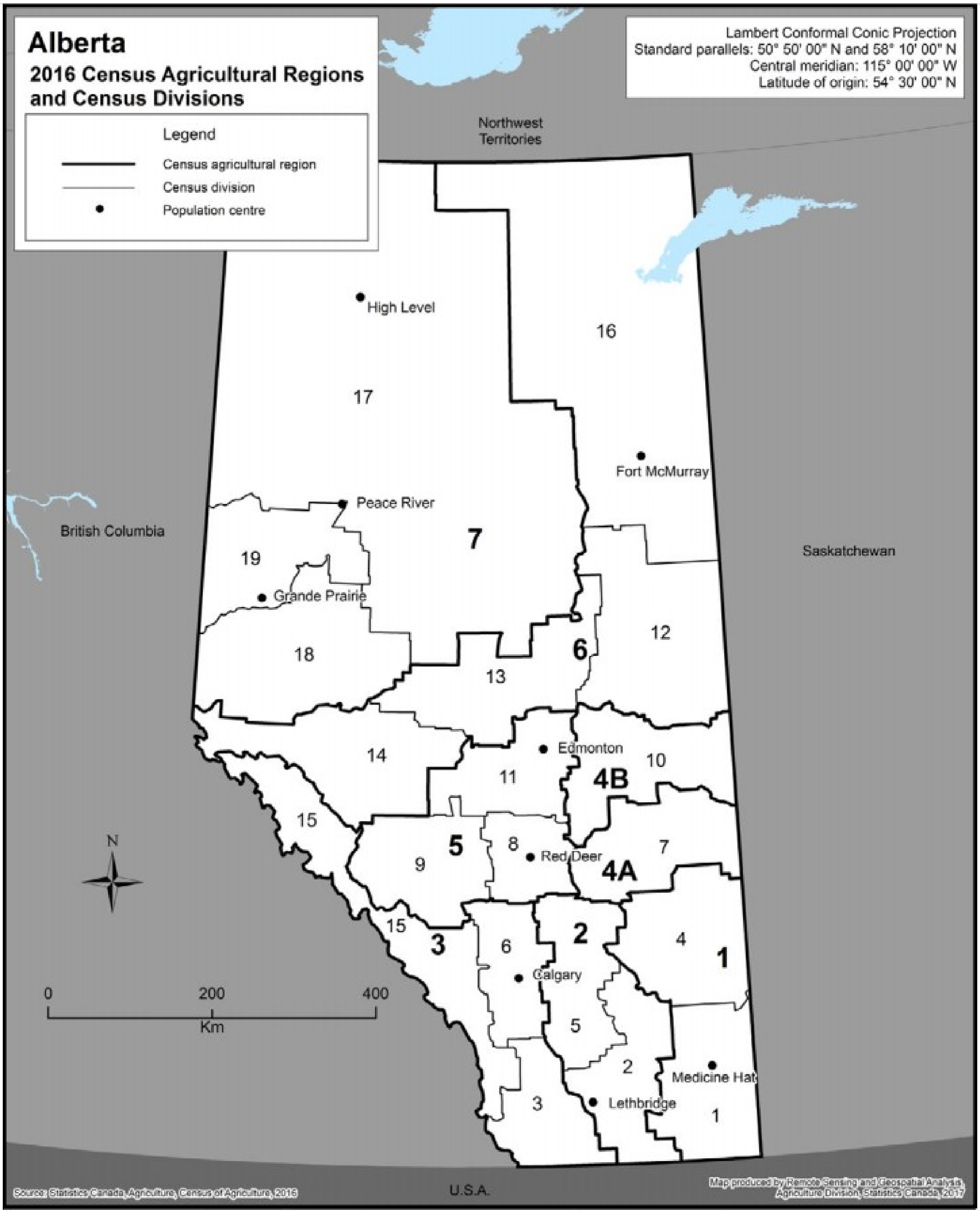


Figure F.1 Map of agricultural regions in Alberta (Statistics Canada 2017b)

Appendix G. Model Results when Herd Size is Included as an Input

Table G.1 Maximum likelihood parameter estimates: Hyperbolic distance function with and without GHGs, and including herd size as an input

	GHG		No GHG	
	Estimate[a]	Std. Error[b]	Estimate[a]	Std. Error[b]
Intercept	-0.0476***	0.0143	-0.0514***	0.0145
Linear time trend	-0.0029	0.0021	-0.0016	0.0021
Quadratic time trend	-0.0001	0.0001	-0.0001	0.0001
Forage[c]	0.0187	0.0119	0.0137	0.0121
Concentrate	-0.0247**	0.0124	-0.0337***	0.0121
Labour	-0.0077	0.0097	-0.0099	0.0105
Capital	-0.0076	0.0096	-0.0138	0.0102
Other	-0.0510***	0.0145	-0.0494***	0.0127
Herd size	-0.3831***	0.0280	-0.4218***	0.0201
Livestock sales	0.0159*	0.0081	0.0155*	0.0079
LivestockSales*LivestockSales	0.0108	0.0074	0.0097	0.0072
LivestockSales*Forage	-0.0199	0.0177	-0.0149	0.0166
LivestockSales*Concentrate	-0.0184	0.0154	-0.0127	0.0149
LivestockSales*Labour	-0.0690**	0.0336	-0.0620*	0.0321
LivestockSales*Capital	-0.0107	0.0127	-0.0089	0.0133
LivestockSales*Other	0.0192	0.0175	0.0183	0.0180
LivestockSales*HerdSize	0.0601	0.0487	0.0710	0.0466
Forage*Forage	-0.0037	0.0150	-0.0054	0.0142
Forage*Concentrate	-0.0091	0.0208	-0.0062	0.0206
Forage*Labour	-0.0205	0.0244	-0.0263	0.0258
Forage*Capital	0.0193	0.0192	0.0169	0.0200
Forage*Other	0.0137	0.0260	0.0241	0.0267
Forage*HerdSize	-0.0329	0.0604	-0.0059	0.0431
Concentrate*Concentrate	-0.0063	0.0142	-0.0109	0.0122
Concentrate*Labour	0.0011	0.0255	0.0165	0.0249
Concentrate*Capital	-0.0107	0.0197	-0.0103	0.0192
Concentrate*Other	0.0147	0.0237	0.0154	0.0217
Concentrate*HerdSize	0.0166	0.0518	0.0136	0.0359
Labour*Labour	-0.0165	0.0207	-0.0095	0.0211
Labour*Capital	0.0334	0.0209	0.0381*	0.0220
Labour*Other	-0.0072	0.0265	-0.0133	0.0268
Labour*HerdSize	-0.0244	0.0733	0.0103	0.0565
Capital*Capital	-0.0033	0.0118	-0.0066	0.0119
Capital*Other	-0.0400*	0.0230	-0.0358	0.0221

Capital*HerdSize	0.0078	0.0468	0.0108	0.0330
Other*Other	0.0320*	0.0191	0.0283	0.0189
Other*HerdSize	-0.0236	0.0644	-0.0391	0.0458
HerdSize*HerdSize	0.0084	0.1075	-0.0072	0.0530
GHG	-0.0585**	0.0239		
GHG*GHG	-0.0027	0.0483		
GHG*Livestock	0.0284	0.0360		
GHG*Forage	0.0288	0.0481		
GHG*Concentrate	0.0027	0.0469		
GHG*Labour	0.0531	0.0609		
GHG*Capital	0.0007	0.0427		
GHG*Other	-0.0128	0.0574		
GHG*HerdSize	-0.0208	0.1316		
Joint Inefficiency Model				
Intercept	0.7033***	0.0842	0.7006***	0.0847
Herd size	0.0002**	0.0001	0.0003*	0.0001
Milk yield	-0.0366***	0.0034	-0.0371***	0.0036
Linear time trend	0.0003	0.0041	-0.0017	0.0039
Quadratic time trend	0.0003	0.0002	0.0004*	0.0002
Butterfat	-0.0088	0.0158	-0.0052	0.0177
Years farming	0.0003	0.0005	0.0003	0.0004
Proportion of paid labour	0.0032	0.0129	0.0060	0.0132
Proportion of purchased feed	0.0090	0.0145	0.0123	0.0157
Debt to asset ratio	-0.0466	0.2655	0.0267	0.2178
North/South dummy (North = 1)	0.0012	0.0065	-0.0020	0.0081
Proportion of forage in diet	-0.0902	0.0709	-0.0924	0.0695
σ^2	0.0020***	0.0006	0.0021***	0.0006
γ	0.7941***	0.0446	0.7840***	0.0493
Log likelihood ratio	2223.01		2021.911	

[a] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b] standard errors derived from bootstrapping with 2000 replications
[c] with the exception of the intercept, inefficiency model variables, and time trends, the variables are natural logarithms

Appendix H: Survey Forms for the Alberta Dairy Cost Study

Monthly forms

DAIRY COST STUDY, 2015 — Confidential

Monthly Reporting Sheet

Name: ____________________

Month: ____________________

If you have any questions, please call Pauline Van Biert at 780-415-2153, toll free by first dialing 310-0000

Dairy Herd	Beginning No.	Purchases No.	Purchases Total Value	No. Born	Died or Trans/Out	Sales No.	Sales Total Value	End No.
1 Milking Cows								
2 Dry Cows								
3 Bred Heifers								
4 Open Heifers								
5 Heifer Calves								
6 Bull Calves*								
7 Herd Bulls								

***less than 6 months**

Capital Purchases		Specify	Total Value ($)	% to Dairy	% to Other Farm
1 Equipment	*Purchases:*				
2	*Sales:*				
3 Tractor/Truck	*Purchases:*				
4	*Sales:*				
5 Buildings	*Purchases/Const:*				
6	*Sales:*				
13 TPQ	*Purchased:*	(kgs/day)			
14	*Sold:*	(kgs/day)			
16 Credit Transfers		($/kg)			

Milk Produced / Sold *	Litres	Total $ Value
2 Milk Fed To Livestock		
3 Milk Used in the Home		
4 Unuseable Milk (dumped)		
5 Miscellaneous Dairy Income (i.e. colostrum sales, BSE program pmts.)		

*** All Plant Sales will be recorded from Milk Statement provided by Alberta Milk**

	FEED Used by Dairy Herd	Office Use	Unit Type*	Bale Weight	Amount Used	Unit Price (if purchased)	Cd		Office Use	Unit Type *	Amount Used	Unit Price
1	Barley						21	Dairy Ration				
2	Oats						22	Supplement				
3	Wheat						23	Brew Grain				
5	Hay (homegrown)						24	Beet Pulp				
6	Hay (purchased)						25	Alfalfa Pellets				
7	Silage						26	Calf Feed				
8	Haylage						27	Milk Replacer				
9	Greenfeed						28	Salt				
10	Straw - Fed						29	Min. & Vit.				
11	Straw-Bedding											
11	Sawdust											
12	Other:						31	Grinding & Processing				

* T = Imperial Ton, t = Metric tonne, bu = bushels, kg = kilograms,
ba = bales (please provide bale weight), bags (20 or 25 kg)

	LABOUR for Dairy Activities *		Total Hours	Wages & Board
1	Operator			
2	Wife, Partner, 2nd Operator			
3	Family Labour	*16 yrs and Over*		
4		*Under 16*		
5	Hired Labour	*1*		
5		*2*		

* do not include hours doing fieldwork

	EXPENSES		Total Farm ($)	% to Dairy	% Other Farm
1	Veterinary and Medicine				
1	Breeding				
2	Livestock & Barn Supplies				
3	Building & Fence Repair				
4	Machinery & Equipment Repair				
5	Fuel, Oil, Lube	(for equipment, not heating)			
13	Natural Gas				
14	Electricity				
15	Other Utilities	(phone, propane, heating oil, etc.)			
7	Insurance, Licences & Taxes				
8	Cash Rental	(pasture, equipment, leases, etc.)			
9	Operating Loan Interest				
10	Custom Work (i.e. manure hauling, parlour cleaning)				
11	Silage Bags	(hay tarps, plastic, etc.)			
12	Misc.	(legal, acct, D.H.I., hooftrimming, etc)			
12					

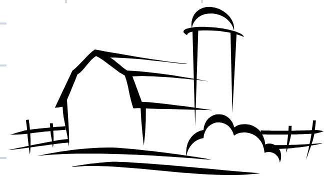
Confidential when Completed

Annual forms

DAIRY COST STUDY, 2015

Confidential

Investments and Liabilities



General Information

Contact Name:		TPQ Holdings kg/day: (January 2015)	
E-Mail:		Number of Years in Dairy	
Fax:			

Land Information	Total Acres	$ per Acre	% to Dairy	% to Other Farm
Building Site				
Pasture				
Crop / Hay Land				

	Farm Loans	Balance: Jan. 1, 2015	Interest Rate	% to Dairy	% to Other Farm
1	Land:				
1					
2	Building:				
2					
3	Livestock:				
3					
4	Machinery:				
4					
5	Other:				

Notice of Collection:
The personal information, on this form, is being collected for the purpose of conducting research on the costs and returns of agricultural production in Alberta. The collection is under the authority of section 33 of the *Freedom of Information and Protection of Privacy* (FOIP) *Act* and is subject to the provisions of the Act. Only aggregated, non-identifying, information will be published and made available to the general public or organizations for research purposes.

If you have any questions about the collection or use of the information, please contact the Director, Economics Branch, Alberta Agriculture and Rural Development, #303, 7000 - 113 Street, Edmonton, Alberta, T6H 5T6 or phone: 780-422-3771

DAIRY COST STUDY, 2015

Name: ______________________________

Supplies Inventory, Machinery and Buildings, January 1, 2015

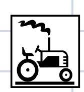
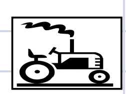
Supplies Inventory			% to Dairy	% to Other Farm
		Value: Jan. 1, 2015		
1	Gas, Oil & Grease			
2	Vet., Semen, Etc			
3	Bedding			
4	Dairy Livestock Supplies (ie. pails)			
5	Rations & Supplements			
6	Other Supplies (ie. filters, soaps, etc.)			

Buildings Used for Dairy:		Purchased Price	Year Purchased	% to Dairy	% to Other Farm
1					
1					
1					
1					
1					
1					
1					
1					
1					

Examples: barns, machine shed, hay sheds, bunkers, shop, calf hutches, corrals

Tractors & Trucks Used for Dairy:					
2					
2					
2					
2					
2					
2					
2					
2					

If you have any questions, please call Pauline Van Biert at 780-415-2153, toll free by first dialing 310-0000

see over

Dairy Equipment:

3					
3					
3					
3					
3					
3					
3					
3					
3					
3					

Examples: bulk tank, pipeline, milk meters, washer, vacuum pump, generator, buckets

Other Equipment Used for Dairy:		Purchased Price	Year Purchased	% to Dairy	% to Other Farm
4					
4					
4					
4					
4					
4					
4					
4					
4					
4					
4					
4					
4					
4					
4					

Examples: manure spreader, barn cleaner, manure pump, cattle trailer, quad, bale feeders, silo unloader, scraper, feed mixers, sawdust blowers, semen tank, fencers, fans, crowd gate, small tools (table saw, drill press, welder, power tools), fuel tanks, wheel barrows, computer feeding system, home computer

Appendix I: Alternative Models to Account for Outlying Production Levels in 2008

Table I.1 Maximum likelihood parameter estimates: Hyperbolic distance function with and without GHGs when revenue is used instead of production for milk output

	GHG		No GHG	
	Estimate[a]	Std. Error[b]	Estimate[a]	Std. Error[b]
Intercept	0.0427***	0.0120	0.1200***	0.0141
Linear time trend	-0.0004	0.0045	-0.0105**	0.0049
Quadratic time trend	-0.0011***	0.0003	-0.0010***	0.0003
Forage[c]	-0.0164	0.0128	-0.0378***	0.0146
Concentrate	-0.0221	0.0136	-0.0573***	0.0144
Labour	-0.0328***	0.0084	-0.0506***	0.0098
Capital	-0.0915***	0.0116	-0.1880***	0.0114
Other	-0.0805***	0.0098	-0.1157***	0.0122
Livestock sales	0.0225***	0.0048	0.0259***	0.0055
LivestockSales*LivestockSales	0.0081*	0.0042	0.0049	0.0044
LivestockSales*Forage	-0.0167	0.0166	0.0122	0.0166
LivestockSales*Concentrate	-0.0230	0.0151	0.0037	0.0159
LivestockSales*Labour	-0.0687**	0.0180	-0.0595***	0.0226
LivestockSales*Capital	-0.0124	0.0108	-0.0005	0.0133
LivestockSales*Other	0.0027	0.0179	0.0406*	0.0215
Forage*Forage	0.0014	0.0173	0.0152	0.0163
Forage*Concentrate	-0.0939***	0.0227	-0.0468**	0.0232
Forage*Labour	-0.0408	0.0297	-0.0038	0.0309
Forage*Capital	0.0153	0.0194	0.0041	0.0204
Forage*Other	0.0149	0.0356	-0.0100	0.0339
Concentrate*Concentrate	0.0197	0.0132	0.0053	0.0123
Concentrate*Labour	-0.0489*	0.0283	0.0091	0.0292
Concentrate*Capital	-0.0221	0.0149	-0.0178	0.0148
Concentrate*Other	0.0497**	0.0251	0.0630**	0.0258
Labour*Labour	0.0001	0.0242	0.0055	0.0241
Labour*Capital	0.0645***	0.0179	0.0533***	0.0195
Labour*Other	-0.0876***	0.0370	-0.0821**	0.0361
Capital*Capital	0.0381***	0.0101	0.0207**	0.0105
Capital*Other	-0.0227	0.0216	-0.0912***	0.0269
Other*Other	0.0608***	0.0212	0.0779**	0.0277
GHG	-0.2414***	0.0184		
GHG*GHG	0.0126	0.0580		
GHG*Livestock	0.1159***	0.0318		
GHG*Forage	0.0707	0.0494		
GHG*Concentrate	0.0835**	0.0418		

GHG*Labour	0.0918	0.0648		
GHG*Capital	-0.1338***	0.0328		
GHG*Other	-0.0710	0.0613		
Joint Inefficiency Model				
Intercept	0.0021	0.0726	0.0466	0.0737
Herd size	0.0003***	0.0001	0.0003**	0.0001
Milk yield	-0.0165***	0.0020	-0.0208***	0.0027
Linear time trend	0.0006	0.0080	0.0030	0.0093
Quadratic time trend	0.0003	0.0005	0.0002	0.0006
Butterfat	0.0659***	0.0170	0.0608***	0.0175
Years farming	0.0008**	0.0004	0.0010*	0.0005
Proportion of paid labour	-0.0225	0.0185	0.0039	0.0232
Proportion of purchased feed	0.0054	0.0186	0.0598***	0.0222
Debt to asset ratio	0.2851	0.2533	0.5427	0.3649
North/South dummy (North = 1)	0.0056	0.0079	-0.0042	0.0092
Proportion of forage in diet	-0.0164	0.0970	-0.0183	0.1099
σ^2	0.0052***	0.0008	0.0071***	0.0013
γ	0.8025***	0.0677	0.7865***	0.0682
Log likelihood ratio	1692.978		1519.624	

[a] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b] standard errors derived from bootstrapping with 2000 replications
[c] with the exception of the intercept, inefficiency model variables, and time trends, the variables are natural logarithms

Table I.2 Maximum likelihood parameter estimates: Hyperbolic distance function with and without GHGs including a dummy variable for the year 2008[a]

	GHG		Without GHG	
	Estimate[b]	Std. Error[c]	Estimate[b]	Std. Error[c]
Intercept	-0.0067	0.0216	0.0817***	0.0154
2008 dummy (1 = 2008)	0.0797***	0.0258	0.1049***	0.0298
Linear time trend	-0.0002	0.0040	-0.0101***	0.0027
Quadratic time trend	-0.0007***	0.0002	-0.0007***	0.0002
Forage[d]	-0.0075	0.0110	-0.0384***	0.0112
Concentrate	-0.0291***	0.0107	-0.0690***	0.0105
Labour	-0.0273***	0.0081	-0.0498***	0.0089
Capital	-0.0708***	0.0122	-0.1926***	0.0103
Other	-0.0572***	0.0105	-0.0853***	0.0099
Livestock sales	0.0209***	0.0056	0.0237***	0.0068
LivestockSales*LivestockSales	0.0079	0.0052	0.0084	0.0069
LivestockSales*Forage	-0.0044	0.0148	0.0068	0.0140
LivestockSales*Concentrate	-0.0111	0.0133	0.0012	0.0142
LivestockSales*Labour	-0.0599**	0.0257	-0.0603**	0.0287
LivestockSales*Capital	0.0139	0.0164	0.0230	0.0196
LivestockSales*Other	-0.0095	0.0164	0.0157	0.0199
Forage*Forage	-0.0054	0.0151	0.0038	0.0136
Forage*Concentrate	-0.0723***	0.0231	-0.0168	0.0221
Forage*Labour	-0.0288	0.0278	-0.0109	0.0287
Forage*Capital	0.0119	0.0204	-0.0067	0.0175
Forage*Other	-0.0221	0.0310	0.0085	0.0291
Concentrate*Concentrate	0.0085	0.0128	-0.0074	0.0110
Concentrate*Labour	-0.0332	0.0276	0.0368	0.0256
Concentrate*Capital	-0.0202	0.0152	-0.0259	0.0133
Concentrate*Other	-0.0118	0.0249	0.0374	0.0229
Labour*Labour	-0.0255	0.0237	-0.0258	0.0234
Labour*Capital	0.0648***	0.0189	0.0614***	0.0167
Labour*Other	-0.0709*	0.0368	-0.0466	0.0329
Capital*Capital	0.0379***	0.0126	0.0224**	0.0103
Capital*Other	-0.0169	0.0221	-0.0734***	0.0240
Other*Other	0.0376*	0.0204	0.0442*	0.0246
GHG	-0.2862***	0.0179		
GHG*GHG	-0.0559	0.0553		
GHG*Livestock	0.0591*	0.0302		
GHG*Forage	0.0963**	0.0473		
GHG*Concentrate	0.1240***	0.0421		

GHG*Labour	0.0941*	0.0527		
GHG*Capital	-0.1396***	0.0389		
GHG*Other	0.0301	0.0619		
Joint Inefficiency Model				
Intercept	0.4891***	0.0981	0.7037***	0.1127
Herd size	0.0001	0.0001	0.0001	0.0001
Milk yield	-0.0262***	0.0030	-0.0340***	0.0040
Linear time trend	-0.0002	0.0058	-0.0028	0.0040
Quadratic time trend	0.0005*	0.0003	0.0006***	0.0002
Butterfat	-0.0168	0.0181	-0.0456*	0.0245
Years farming	0.0010**	0.0004	0.0010*	0.0005
Proportion of paid labour	0.0147	0.0152	0.0175	0.0177
Proportion of purchased feed	0.0322*	0.0165	0.0704**	0.0291
Debt to asset ratio	0.2279	0.2472	0.5569	0.3389
North/South dummy (North = 1)	0.0128*	0.0067	-0.0014	0.0094
Proportion of forage in diet	-0.0811	0.0706	-0.0785	0.0810
σ^2	0.0029***	0.0006	0.0048***	0.0010
γ	0.7104***	0.0683	0.6910***	0.0664
Log likelihood ratio	1913.154		1705.54	

[a]The parameter statistical significances are comparable to the model with 2008 observations removed; however, this model had low efficiencies for the year 2008 and many bootstrap iterations reported "wrong skewness"
[b] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[c] standard errors derived from bootstrapping with 2000 replications
[d] with the exception of the intercept, inefficiency model variables, and time trends, the variables are natural logarithms

Appendix J: Data Envelopment Analysis Model Variations

4 sets of models are estimated for each DEA expression:

1. Variable returns to scale (VRS), all outputs
2. VRS, just milk (livestock omitted)
3. Constant returns to scale (CRS), all outputs
4. CRS, just milk

DEA Expression 1: Enhanced Hyperbolic Distance Function

$$D_H(\boldsymbol{x}', \boldsymbol{y}', \boldsymbol{b}') = \inf\{\theta' \geq 0: \left(\boldsymbol{x}'\theta', \frac{\boldsymbol{y}'}{\theta'}, \boldsymbol{b}'\theta'\right)\} \quad s.t. \tag{J.1}$$

$$\sum_{i=1}^{I} \lambda_i y_{im} \geq \frac{y'_{im}}{\theta'},\ m = 1, \ldots, M$$

$$\sum_{i=1}^{I} \lambda_i b_{ir} = b'_{ir}\theta',\ r = 1, \ldots, R$$

$$\sum_{i=1}^{I} \lambda_i x_{in} \leq \frac{x'_{in}}{\theta'},\ n = 1, \ldots, N$$

$$For\ VRS\ \sum_{i=1}^{I} \lambda_i = 1$$

$$For\ CRS\ \sum_{i=1}^{I} \lambda_i \geq 0$$

1. VRS, all outputs
   - Tobit model did not converge for GHG model (No GHG model is the same as DEA Expression 3)
2. VRS, just milk
   - GHG efficiency: 5 producers did not have full efficiency (range from 0.901-0.959, mean = 0.986, SD = 0.03)
   - No GHG efficiency: Same 5 producers did not have full efficiency (range from 0.886-0.959, mean = 0.984, SD = 0.04)

Table J.1 Parameter estimates for the enhanced hyperbolic distance function using VRS and just milk (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	-1.4172*	-5.0299	-2.2348	-0.8209*	-3.6383	-1.4015
Herd Size	0.0009*	0.0012	0.0022	0.0007*	0.0009	0.0018
Milk Yield	0.0430*	0.0682	0.1024	0.0351*	0.0550	0.0843
Butterfat	0.4187*	0.5199	1.1557	0.3021*	0.3498	0.8695
Years farming	0.0061*	0.0070	0.0174	0.0051*	0.0060	0.0142
Proportion of paid labour	-0.2640*	-0.7510	-0.2807	-0.2179*	-0.6230	-0.2285
Proportion of purchased feed	-0.2636*	-0.8359	-0.1675	-0.1866*	-0.6234	-0.1004
Debt to asset ratio	6.2565*	8.6996	16.9029	4.8084*	6.5122	12.9993
North/South dummy (North = 1)	-0.2883*	-0.6923	-0.4571	-0.2416*	-0.5769	-0.3803

3. CRS, all outputs
    - GHG efficiency: 3 producers not at the frontier (range from 0.811-0.995, mean = 0.989, SD = 0.04)
    - No GHG efficiency: 7 producers not at the frontier (range from 0.788-0.998, mean = 0.982, SD = 0.046)

Table J.2 Parameter estimates for the enhanced hyperbolic distance function using CRS and all outputs (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	0.7551*	0.0738	1.2164	-2.4339*	-7.4972	-3.6126
Herd Size	0.0006*	0.0009	0.0013	0.0006*	0.0005	0.0018
Milk Yield	0.0151*	0.0218	0.0366	0.0453*	0.0646	0.1134
Butterfat	0.0067	-0.1245	0.1370	0.6702*	0.8640	1.7544
Years farming	0.0000	-0.0018	0.0021	0.0122*	0.0181	0.0308
Proportion of paid labour	0.0105	-0.0733	0.1112	0.0734	-0.1601	0.4736
Proportion of purchased feed	-0.1638*	-0.4553	-0.1899	-0.6969*	-1.7850	-0.8920
Debt to asset ratio	-0.2002	-1.8387	1.4447	10.3829*	15.2538	26.1874
North/South dummy (North = 1)	-0.0170	-0.0810	0.0126	-0.2955*	-0.7488	-0.4305

4. CRS, just milk
    - GHG efficiency: 6 producers did not have full efficiency (range from 0.802-0.951, mean = 0.976, SD = 0.051)
    - No GHG efficiency: 9 producers did not have full efficiency (range from 0.778-0.985, mean = 0.964, SD = 0.066)

Table J.3 Parameter estimates for the enhanced hyperbolic distance function using CRS and just milk (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	0.4510	-0.5091	0.5175	-3.0374*	-8.7674	-4.6182
Herd Size	-0.0001	-0.0003	0.0002	0.0011*	0.0015	0.0030
Milk Yield	0.0178*	0.0260	0.0395	0.0630*	0.0973	0.1516
Butterfat	0.0691*	0.0167	0.2592	0.7289*	0.9702	1.9225
Years farming	0.0011*	0.0004	0.0040	0.0079*	0.0085	0.0233
Proportion of paid labour	0.0055	-0.0923	0.0809	-0.3623*	-1.0643	-0.3487
Proportion of purchased feed	-0.0566*	-0.2301	-0.0054	-0.2425	-0.9590	0.0249
Debt to asset ratio	0.0706	-1.0857	2.0927	5.6693*	5.8905	17.9476
North/South dummy (North = 1)	-0.0846*	-0.2024	-0.1155	-0.4032*	-0.9839	-0.6359

DEA Expression 2: Output Oriented Hyperbolic

$$D_H(\boldsymbol{x}', \boldsymbol{y}', \boldsymbol{b}') = \inf\{\theta' \geq 0: \left(\boldsymbol{x}', \frac{\boldsymbol{y}'}{\theta'}, \boldsymbol{b}'\theta'\right)\} \quad s.t. \tag{J.2}$$

$$\sum_{i=1}^{I} \lambda_i y_{im} \geq \frac{y'_{im}}{\theta'},\ m = 1, \dots, M$$
$$\sum_{i=1}^{I} \lambda_i b_{ir} = b'_{ir}\theta',\ r = 1, \dots, R$$
$$\sum_{i=1}^{I} \lambda_i x_{in} \leq x'_{in},\ n = 1, \dots, N$$
$$For\ VRS\ \sum_{i=1}^{I} \lambda_i = 1$$
$$For\ CRS\ \sum_{i=1}^{I} \lambda_i \geq 0$$

1. VRS, all outputs
   - Tobit model did not converge
2. VRS, just milk
   - GHG efficiency: 5 producers did not have full efficiency (range from 0.751-0.956, mean = 0.972, SD = 0.065)
   - No GHG efficiency: 5 producers did not have full efficiency (range from 0.584-0.936, mean = 0.957, SD = 0.105)

Table J.4 Parameter estimates for the output hyperbolic distance function using VRS and just milk (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	-5.6399*	-14.8404	-8.8798	-3.2617*	-8.4462	-6.3488
Herd Size	0.0024*	0.0037	0.0060	0.0016*	0.0031	0.0028
Milk Yield	0.1195*	0.2005	0.2771	0.0775*	0.1619	0.1590
Butterfat	1.1678*	1.6486	3.0238	0.7402*	1.7441	1.2590
Years farming	0.0153*	0.0195	0.0416	0.0105*	0.0226	0.0248
Proportion of paid labour	-0.6434*	-1.7846	-0.7827	-0.4349*	-0.9355	-0.8484
Proportion of purchased feed	-0.8821*	-2.4113	-1.0704	-0.5649*	-1.0180	-1.4468
Debt to asset ratio	18.0761*	27.6527	43.9382	11.5955*	24.8559	27.4141
North/South dummy (North = 1)	-0.7762*	-1.7991	-1.2883	-0.4952*	-1.1352	-0.9518

3. CRS, all outputs
   - GHG efficiency: 7 producers not at the frontier (range from 0.746-0.995, mean = 0.969, SD = 0.065)
   - No GHG efficiency: 6 producers not at the frontier (range from 0.463-0.969, mean = 0.960, SD = 0.113)

Table J.5 Parameter estimates for the output hyperbolic distance function using CRS and all outputs (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	0.9064	-0.3451	2.5751	0.8697*	0.1411	1.6936
Herd Size	0.0015*	0.0025	0.0036	0.0007*	0.0011	0.0017
Milk Yield	0.0468*	0.0705	0.1096	0.0214*	0.0312	0.0518
Butterfat	-0.1132	-0.5726	0.0977	-0.0472	-0.2848	0.0709
Years farming	-0.0035*	-0.0121	-0.0018	-0.0002	-0.0030	0.0022
Proportion of paid labour	0.0134	-0.2078	0.2656	0.0277	-0.0737	0.1907
Proportion of purchased feed	-0.5175*	-1.3769	-0.6898	-0.1593*	-0.5020	-0.1221
Debt to asset ratio	-2.7784*	-9.1925	-1.0002	-1.6779*	-5.0737	-0.1431
North/South dummy (North = 1)	0.0701*	0.0125	0.2564	-0.0305	-0.1270	0.0032

4. CRS, just milk
    - GHG efficiency: 9 producers not at the frontier (range from 0.734-0.951, mean = 0.944, SD = 0.091)
    - No GHG efficiency: 9 producers not at the frontier (range from 0.427-0.985, mean = 0.918, SD = 0.162)

Table J.6 Parameter estimates for the output hyperbolic distance function using CRS and just milk (α = 0.05)

	No GHG	Confidence Interval		GHG	Confidence Interval	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	-0.4255*	-2.8711	-0.3560	0.4021	-0.7154	0.6158
Herd Size	-0.0003	-0.0007	0.0004	-0.0003	-0.0005	0.0001
Milk Yield	0.0439*	0.0651	0.0972	0.0237*	0.0345	0.0520
Butterfat	0.1933*	0.0844	0.6839	0.0556*	-0.0449	0.2575
Years farming	0.0025*	0.0008	0.0094	0.0014*	0.0006	0.0051
Proportion of paid labour	0.0127	-0.2175	0.2052	0.0153	-0.1125	0.1098
Proportion of purchased feed	-0.1884*	-0.6610	-0.0799	-0.0185	-0.2013	0.1008
Debt to asset ratio	0.6696	-1.7286	5.9514	-1.1775	-3.6143	0.8308
North/South dummy (North = 1)	-0.1934*	-0.4660	-0.2574	-0.1084*	-0.2561	-0.1443

DEA Expression 3: GHG as input

$$D_H(\boldsymbol{x}', \boldsymbol{y}', \boldsymbol{b}') = \inf\{\theta' \geq 0: \left(\boldsymbol{x}', \frac{\boldsymbol{y}'}{\theta'}, \boldsymbol{b}'\theta'\right)\} \quad s.t. \tag{J.3}$$

$$\sum_{i=1}^{I} \lambda_i y_{im} \geq \frac{y'_{im}}{\theta'},\ m = 1, \ldots, M$$

$$\sum_{i=1}^{I} \lambda_i b_{ir} \leq b'_{ir}\theta',\ r = 1, \ldots, R$$

$$\sum_{i=1}^{I} \lambda_i x_{in} \leq x'_{in},\ n = 1, \ldots, N$$

$$For\ VRS\ \sum_{i=1}^{I} \lambda_i = 1$$

$$For\ CRS\ \sum_{i=1}^{I} \lambda_i \geq 0$$

1. VRS, all outputs
    - GHG efficiency: 4 producers do not have full efficiency, with efficiencies ranging from 0.8908-0.9940 (Mean = 0.9923, SD = 0.024)
    - No GHG efficiency: 4 producers do not have full efficiency, with efficiencies ranging from 0.888-0.994 (Mean = 0.9922, SD = 0.024)

Table J.7 Parameter estimates for GHG as an input using VRS and all outputs (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	0.9245	-0.1861	2.2654	0.9285	-0.1923	2.2402
Herd Size	0.0014*	0.0024	0.0034	0.0014*	0.0024	0.0033
Milk Yield	0.0101*	0.0043	0.0361	0.0100*	0.0033	0.0353
Butterfat	-0.0354	-0.3658	0.2151	-0.0354	-0.3579	0.2113
Years farming	0.0022	-0.0001	0.0089	0.0021	0.0000	0.0086
Proportion of paid labour	-0.1454*	-0.5022	-0.0618	-0.1432*	-0.4926	-0.0591
Proportion of purchased feed	-0.2733*	-0.8130	-0.2463	-0.2688*	-0.8091	-0.2321
Debt to asset ratio	2.6249*	1.7761	9.1366	2.5771*	1.7863	9.0524
North/South dummy (North = 1)	0.0654*	0.0259	0.2425	0.0645*	0.0268	0.2381

2. VRS, just milk
   - GHG efficiency: 5 producers did not have full efficiency (range from 0.885-0.960, mean = 0.984, SD = 0.035)
   - No GHG efficiency: (same as expression 1) Same 5 producers did not have full efficiency (range from 0.886-0.959, mean = 0.984, SD = 0.04)

Table J.8 Parameter estimates for GHG as an input using VRS and just milk (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	-0.8209*	-3.9050	-6.1966	-1.3464*	-4.9137	-2.1542
Herd Size	0.0007*	0.0012	0.0015	0.0008*	0.0012	0.0022
Milk Yield	0.0351*	0.0742	0.0741	0.0424*	0.0667	0.1015
Butterfat	0.3021*	0.9289	1.4839	0.4052*	0.5009	1.1217
Years farming	0.0051*	0.0153	0.0157	0.0058*	0.0065	0.0163
Proportion of paid labour	-0.2179*	-0.5329	-0.7980	-0.2595*	-0.7325	-0.2823
Proportion of purchased feed	-0.1866*	-0.3084	-0.1121	-0.2678*	-0.8451	-0.1923
Debt to asset ratio	4.8084*	12.5385	7.5967	6.1655*	8.5644	16.3817
North/South dummy (North = 1)	-0.2416*	-0.6444	-0.5674	-0.2809*	-0.6696	-0.4446

3. CRS, all outputs
    - GHG efficiency: 3 producers not at the frontier (range from 0.811-0.995, mean = 0.989, SD = 0.04)
    - No GHG efficiency: (same as expression 1) 7 producers not at the frontier (range from 0.804-0.997, mean = 0.983, SD = 0.043)

Table J.9 Parameter estimates for GHG as an input using CRS and all outputs (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	0.7551*	0.0738	1.2164	0.7887*	0.1433	1.2183
Herd Size	0.0006*	0.0009	0.0013	0.0005*	0.0009	0.0012
Milk Yield	0.0151*	0.0218	0.0366	0.0141*	0.0204	0.0342
Butterfat	0.0067	-0.1245	0.1370	0.0016	-0.1261	0.1201
Years farming	0.0000	-0.0018	0.0021	0.0000	-0.0018	0.0020
Proportion of paid labour	0.0105	-0.0733	0.1112	0.0113	-0.0613	0.1120
Proportion of purchased feed	-0.1638*	-0.4553	-0.1899	-0.1474*	-0.4118	-0.1651
Debt to asset ratio	-0.2002	-1.8387	1.4447	-0.2975	-1.9878	1.1748
North/South dummy (North = 1)	-0.0170	-0.0810	0.0126	-0.0166	-0.0774	0.0120

4. CRS, just milk
    - GHG efficiency: 9 producers did not have full efficiency (range from 0.785-0.985, mean = 0.965, SD = 0.063)
    - No GHG efficiency: (same as expression 1) 9 producers did not have full efficiency (range from 0.778-0.985, mean = 0.964, SD = 0.066)

Table J.10 Parameter estimates for GHG as an input using CRS and only milk (α = 0.05)

	No GHG	**Confidence Interval**		**GHG**	**Confidence Interval**	
	Estimate	lower bound	upper bound	Estimate	lower bound	upper bound
Intercept	0.4510	-0.5091	0.5175	0.5006	-0.3989	0.5521
Herd Size	-0.0001	-0.0003	0.0002	-0.0002	-0.0003	0.0001
Milk Yield	0.0178*	0.0260	0.0395	0.0168*	0.0243	0.0369
Butterfat	0.0691*	0.0167	0.2592	0.0600*	0.0104	0.2324
Years farming	0.0011*	0.0004	0.0040	0.0011*	0.0005	0.0040
Proportion of paid labour	0.0055	-0.0923	0.0809	0.0066	-0.0817	0.0758
Proportion of purchased feed	-0.0566*	-0.2301	-0.0054	-0.0450	-0.2044	0.0220
Debt to asset ratio	0.0706	-1.0857	2.0927	-0.0308	-1.1654	1.9204
North/South dummy (North = 1)	-0.0846*	-0.2024	-0.1155	-0.0824*	-0.1934	-0.1137

Appendix K: Questionnaire for Detailed Dataset

Supplemental Dairy Efficiency Survey

This survey is designed to determine the relationship between Greenhouse Gas (GHG) emissions and productive efficiency for dairy farms in Alberta. We would like to learn about the management details of your dairy and associated crop and forage enterprise so that links between production costs, GHG emission, carbon footprint and productive efficiency can be assessed. The questions cover the same time period of the AAF Cost Study (January 1 to December 31, 2016) and relate to the management of different animal groups in your enterprise.

A. Animal Management

1. What type of milking system do you have? Parlour _____Robotic ____ Other (please specify) ______________

2. How many times are the cows milked per day? 1 ___ 2 ___ 3 ___ 4 or more ____

3. On an annual basis, what is the average milk production per cow per day? ___________ (please include units, lb or kg)

4. On an annual average basis, what is the fat content (%) of produced milk? _______ (%)

5. On an annual average basis, what is the protein content (%) of produced milk? _______ (%)

6. What is the average weight per animal for the following suggested animal groups? Please revise suggested group name and/or add extra categories as appropriate for your operation. <u>If average weight per animal is not known for any of the group categories, instead please provide the predominant breed of animal in that category.</u>

Animal Group	Average Weight	Animal Group	Average Weight
Milking Cows		Young Heifers (< 1 yr)	
Bred Heifers		Dry Cows	
Bulls		Open Cows	
Bull Calves		Other	

What are the units for these weights? Pounds ____ Kilograms ___

7. What is the approximate weight (including units) of young heifers at:
   a) The start of the year: _______
   b) The end of the year: _______

8. How are bull calves managed? Sold ____ Backgrounded ____ Other (please specify) _________

9. What type of housing is primarily used for the following suggested animal groups? Please revise suggested group name and/or add extra categories as appropriate for your operation:

Animal Group	**Free-Stall (✓ if yes)**	**Open Corral (✓ if yes)**	**Other (please specify)**
Milking Cows			
Dry Cows			
Open Cows			
Bred Heifers			
Young Heifers (< 1 yr)			
Bulls			
Bull Calves			

10. Does the housing for any of these animal groups vary during the year? Yes ___ No ___

If yes, please explain:
____

Producer ID: ………………………………

B. Feeding Management

Group 1: Lactating Cows

What are the typical amounts of each type of feed ingredient in the diet for this group of cattle?
Please indicate (check box) if these amounts are per animal or for the group as a whole and whether this is on a daily, weekly or monthly basis:

Per animal □ Whole group □ Daily □ Weekly □ Monthly □

Fresh/Early Lactation Cows

Feed ingredients	**Amount fed (per month)**	**% grown on farm**	**Feed ingredients**	**Amount fed (per month)**	**% grown on farm**
Barley			Supplement		
Oats			Brew Grain		
Wheat			Beet Pulp		
Hay			Alfalfa Pellets		
Silage			Other Ingredients (please specify)		
Haylage					
Greenfeed					
Straw					
Dairy ration					
Salt					

Mid/Late Lactation Cows

Feed ingredients	**Amount fed (per month)**	**% grown on farm**	**Feed ingredients**	**Amount fed (per month)**	**% grown on farm**
Barley			Supplement		
Oats			Brew Grain		
Wheat			Beet Pulp		
Hay			Alfalfa Pellets		
Silage			Other Ingredients (please specify)		
Haylage					
Greenfeed					
Straw					
Dairy ration					
Salt					

1. Is this Group put on pasture for part of the year? Yes _____ No ____
2. If yes, during what months in a typical year is this group on pasture? ___________________________
3. If yes, what is the distance from the barn to the pasture? ___________
   (please indicate units, e.g. feet, meters, miles, kilometers)

Producer ID: ………………………………

Group 2: Dry Cows

What are the typical amounts of each type of feed ingredient in the diet for this group of cattle?
Please indicate (check box) if these amounts are per animal or for the group as a whole and whether this is on a daily, weekly or monthly basis:

Per animal □ Whole group □ Daily □ Weekly □ Monthly □

Close up dry cows (last 3-4 weeks of dry period)

Feed ingredients	Amount fed (per month)	% grown on farm	Feed ingredients	Amount fed (per month)	% grown on farm
Barley			Supplement		
Oats			Brew Grain		
Wheat			Beet Pulp		
Hay			Alfalfa Pellets		
Silage			Other Ingredients (please specify)		
Haylage					
Greenfeed					
Straw					
Dairy ration					
Salt					

Far off dry cows (after last milking until 3-4 weeks of freshening)

Feed ingredients	Amount fed (per month)	% grown on farm	Feed ingredients	Amount fed (per month)	% grown on farm
Barley			Supplement		
Oats			Brew Grain		
Wheat			Beet Pulp		
Hay			Alfalfa Pellets		
Silage			Other Ingredients (please specify)		
Haylage					
Greenfeed					
Straw					
Dairy ration					
Salt					

4. Is this Group put on pasture for part of the year? Yes _____ No ____

5. If yes, during what months in a typical year is this group on pasture? ___________________________

6. If yes, what is the distance from the barn to the pasture? ___________
(please indicate units, e.g. feet, meters, miles, kilometers)

Producer ID: ………………………………

Group 3: Bred Heifers

What are the typical amounts of each type of feed ingredient in the diet for this group of cattle?
Please indicate (check box) if these amounts are per animal or for the group as a whole and whether this is on a daily, weekly or monthly basis:

Per animal □ Whole group □ Daily □ Weekly □ Monthly □

Feed ingredients	Amount fed (per month)	% grown on farm	Feed ingredients	Amount fed (per month)	% grown on farm
Barley			Supplement		
Oats			Brew Grain		
Wheat			Beet Pulp		
Hay			Alfalfa Pellets		
Silage			Other Ingredients (please specify)		
Haylage					
Greenfeed					
Straw					
Dairy ration					
Salt					

7. Is this Group put on pasture for part of the year? Yes _____ No ____

8. If yes, during what months in a typical year is this group on pasture? ___________________________

9. If yes, what is the distance from the barn to the pasture? ___________
(please indicate units, e.g. feet, meters, miles, kilometers)

Group 4: Young Heifers (< 1 year)

What are the typical amounts of each type of feed ingredient in the diet for this group of cattle?
Please indicate (check box) if these amounts are per animal or for the group as a whole and whether this is on a daily, weekly or monthly basis:

Per animal □ Whole group □ Daily □ Weekly □ Monthly □

Feed ingredients	Amount fed (per month)	% grown on farm	Feed ingredients	Amount fed (per month)	% grown on farm
Barley			Supplement		
Oats			Brew Grain		
Wheat			Beet Pulp		
Hay			Alfalfa Pellets		
Silage			Other Ingredients (please specify)		
Haylage					
Greenfeed					
Straw					
Dairy ration					
Salt					

10. Is this Group put on pasture for part of the year? Yes _____ No ____

11. If yes, during what months in a typical year is this group on pasture? ___________________________

12. If yes, what is the distance from the barn to the pasture? ___________
(please indicate units, e.g. feet, meters, miles, kilometers)

Group 5: Bulls (if any)

What are the typical amounts of each type of feed ingredient in the diet for this group of cattle?
Please indicate (check box) if these amounts are per animal or for the group as a whole and whether this is on a daily, weekly or monthly basis:

Per animal □ Whole group □ Daily □ Weekly □ Monthly □

Feed ingredients	Amount fed (per month)	% grown on farm	Feed ingredients	Amount fed (per month)	% grown on farm
Barley			Supplement		
Oats			Brew Grain		
Wheat			Beet Pulp		
Hay			Alfalfa Pellets		
Silage			Other Ingredients (please specify)		
Haylage					
Greenfeed					
Straw					
Dairy ration					
Salt					

13. Is this Group put on pasture for part of the year? Yes _____ No ____

14. If yes, during what months in a typical year is this group on pasture? ___________________________

15. If yes, what is the distance from the barn to the pasture? ___________
(please indicate units, e.g. feet, meters, miles, kilometers)

C. Manure Management

1. What is the primary manure collecting system for your farm? Please select from the following options (circle appropriate response):
    a. Liquid (flush)
    b. Liquid (open lot)
    c. Slurry (slotted floor)
    d. Slurry (scrapers)
    e. Slurry (vacuum)
    f. Solid
    g. Other (please specify) _______________________

    If manure collecting practices vary by animal group, please explain.
    ____

2. What is the primary manure handling practice for your farm? Please select from the following options (circle appropriate response):

a. Anaerobic digester
b. Managed compost (intensive)
c. Unmanaged compost (passive)
d. Deep bedding
e. Liquid earthen
f. Liquid concrete
g. Liquid no crust
h. Liquid crust
i. Pasture
j. Solid storage
k. Daily spread
l. Custom – solid
m. Solid separation (for bedding)
n. Other (please specify)
____

If manure handling practices vary by animal group or by season, please explain.
____

3. Do you spread your own manure or hire it out? _________________________

4. Approximately what amount or percent of your manure is spread on your own land? _____________

5. When you move/apply manure, approximately what percent of your manure storage capacity is emptied each time?__________________________

6. If relevant, what is the method of liquid manure application to cropland?

   a. Broadcast ______
   b. Broadcast and incorporated ______
   c. Banded ______
   d. Injected ______
   e. Other (please specify) ______
   ____

7. If manure is incorporated, how long after application? (please specify units; hours, days, etc.)
____

8. Does your manure handling practice change depending on season? Yes/No
If "yes", please explain:____

9. What is the type of bedding used?
   Straw ______
   Wood Chips ______
   Sand ______
   Gypsum ______
   Other (please specify) ______
   ____

Producer ID: ………………………………

D. Feed Crop Management

Fallow areas and change in land use:

1. What is the fallow area (if any) in your farm in 2016: _________ (acres/ha)

2. Do you use any herbicide on fallow area? Yes/No

3. Have you made any change in the fallow area in the last 12 years?
   a. No
   b. Yes - Increased by _________(acres/ha) in year ______
   c. Yes - Decreased by ________(acres/ha) in year ______

4. Have you converted any long term perennial forage stands into annual crops within the last 12 years?
   a. No
   b. Yes – as part of regular rotation- ______ acres/ha
   c. Yes – different from regular rotation- ____acres/ha in year _______

5. What is the average stand length for perennial forage? _______ (years)

6. Have you broken any grassland/pasture for crop production within the last 12 years? Yes/No

   If yes, please indicate the area of grassland/pasture most recently broken: _______ (acres or ha)
   If yes, please indicate the year grassland/pasture was most recently broken: ________

Producer ID: ………………………………

7. What feed is being grown for use on your farm in 2016? Please indicate the appropriate land area units (acres or hectares) and yield units (bushels, tonnes, etc.). For the following questions, please exclude any crops or hay grown for off farm sales or used in non-dairy enterprises.

Annual Crops								
	Area (acres or ha)	Typical Yield (please specify units)	Typical % Crop Residue left on field	Irrigated? (Yes/No)	Herbicide used? (Yes/No)	Fertilizer N (kg N per acre or ha)	Manure rate (kg per acre or ha)	Phosphorus fertilizer rate (kg P_2O_5 per acre or ha)
Perennial forage crops; for example, grass, legume, mixed hay (please specify)								
	Area (acres or ha)	Typical Yield (please specify units)	Year seeded	Irrigated? (Yes/No)	Herbicide used? (Yes/No)	Fertilizer N (kg N per acre or ha)	Manure rate (kg per acre or ha)	Fertilizer P (kg P2O5 per acre or ha)
Hay (grass)								
Hay (legume)								
Hay (mixed)								
Hay/forage seed								
Grassland; for example, pasture, improved pasture, rangeland, permanent cover, etc. (please specify)								
	Area (acres or ha)	Native grassland? (Yes/No)	Year seeded (if not native)	Irrigated? (Yes/No)		Fertilizer N (kg N per acre or ha)	Manure rate (kg per acre or ha)	Fertilizer P (kg P2O5 per acre or ha)

E. General Producer and Farm Information

1. What is your age? _____ years

2. What is your highest completed level of education?
   Less than high school _____
   High School _____
   Bachelor Degree or Diploma _____
   Graduate Degree _____

3. Approximately what percentage of your total household income is from dairy farming? ____ %

4. How would you classify the predominant soil texture on your farm? Fine/Medium/Coarse

5. What type of soil is prevalent on your farm? Black/Grey /Brown /Dark brown

6. What is your primary current tillage management practice?
   No till ____
   Reduced till ____
   Conventional ____

7. For how long have you been using the current tillage management practice? ______ years

8. What was your previous tillage management practice?
   No till ____
   Reduced till ____
   Conventional ____

9. If your tillage practices vary by type of crop, please explain:

   ____

Appendix L: Alternative SFA Model with Livestock and Forage Ratio Omitted

Table L.1 Maximum likelihood parameter estimates: Hyperbolic distance function with and without GHGs with livestock and forage ratio variables omitted

	GHG		Without GHG	
	Estimate[a]	Std. Error[b]	Estimate[a]	Std. Error[b]
Intercept	-0.0013	0.0154	0.0898***	0.0152
Linear time trend	-0.0061*	0.0033	-0.0125***	0.0030
Quadratic time trend	-0.0002	0.0002	-0.0006***	0.0001
Forage[3]	-0.0049	0.0064	-0.0469***	0.0084
Concentrate	-0.0070***	0.0064	-0.0614***	0.0071
Labour	-0.0514	0.0122	-0.1884***	0.0115
Capital	-0.0213***	0.0071	-0.0515***	0.0102
Other	-0.0380***	0.0077	-0.0887***	0.0090
Forage*Forage	-0.0093	0.0148	-0.0066	0.0123
Forage*Concentrate	-0.0715***	0.0183	-0.0116	0.0200
Forage*Labour	-0.0009	0.0218	-0.0132	0.0237
Forage*Capital	-0.0162	0.0154	-0.0121	0.0177
Forage*Other	0.0651***	0.0249	0.0344	0.0290
Concentrate*Concentrate	0.0226**	0.0098	-0.0082	0.0106
Concentrate*Labour	-0.0438*	0.0237	0.0354	0.0246
Concentrate*Capital	-0.0343***	0.0104	-0.0258**	0.0122
Concentrate*Other	0.0074	0.0202	0.0367	0.0232
Labour*Labour	0.0187	0.0171	-0.0061	0.0196
Labour*Capital	0.0456***	0.0142	0.0462**	0.0195
Labour*Other	-0.0239	0.0269	-0.0526	0.0349
Capital*Capital	0.0252*	0.0146	0.0254*	0.0132
Capital*Other	-0.0494***	0.0179	-0.0670***	0.0225
Other*Other	0.0474***	0.0153	0.0287	0.0224
GHG	-0.3599***	0.0192		
GHG*GHG	-0.0134	0.0459		
GHG*Forage	0.0392	0.0481		
GHG*Concentrate	0.1084***	0.0311		
GHG*Labour	-0.0064	0.0458		

GHG*Capital	-0.0112	0.0315		
GHG*Other	-0.0962**	0.0450		
Joint inefficiency model				
intercept	0.5739***	0.0749	0.7831***	0.1282
Herd size	0.0001	0.0001	0.0000	0.0001
Milk yield	-0.0356***	0.0061	-0.0426***	0.0094
Linear time trend	0.0066	0.0043	0.0015	0.0044
Quadratic time trend	0.0001	0.0002	0.0005**	0.0002
Butterfat	-0.0061	0.0168	-0.0523**	0.0212
Years farming	0.0001	0.0004	0.0008	0.0005
Proportion of paid labour	0.0118	0.0147	0.0201	0.0223
Proportion of purchased feed	0.0312	0.0204	0.1227****	0.0432
Debt to asset ratio	-0.0746	0.2614	0.4019	0.3694
North/South dummy	0.0135*	0.0072	-0.0068	0.0131
Proportion of forage in diet	-0.1703***	0.0577	-0.0857	0.0837
σ^2	0.0038***	0.0011	0.0065***	0.0020
γ	0.8112***	0.0558	0.7586***	0.0693
Log likelihood ratio	1860.246		1571.525	

[a] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b] standard errors derived from bootstrapping with 2000 replications
[c] with the exception of the intercept, inefficiency model variables, and time trends, the variables are natural logarithms