Technology Adoption by Ontario Dairy Producers:

Productivity-enhancing versus Cost-minimizing Technologies

by

Jonathan Okyere Ntoni

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in
Agricultural and Resource Economics

Department of Resource Economics and Environmental Sociology
University of Alberta

ABSTRACT

Under supply management, Canadian dairy producers maximize profits subject to their quota holdings. This constraint on supply effectively leads producers to solve a cost-minimization problem, which may have an effect on their use of technology. I hypothesize that Ontario dairy producers have adopted more cost-minimizing (CM) than productivity-enhancing (PE) technologies. Using data from a 2013 survey of Ontario dairy producers, I characterize technology use in Ontario's dairy industry under the current policy regime and empirically evaluate the effect of various technologies on cow productivity and dairy farm performance. Findings from mean comparison tests show that Ontario producers adopt more CM than PE technologies. Results from propensity score matching and endogenous switching regression models show that the adoption of some PE technologies has positive impact on cow productivity. The adoption of genotyping technology and the use of total mixed rations significantly improve dairy farm performance by reducing feed costs by 8 and 11%, respectively. Overall, my results suggest that producers have adopted technologies that minimize costs. Looking forward, Canadian producers will need not only to consolidate and expand their dairy operations, but will also need to adopt more PE technologies in order to be internationally competitive if supply management weakens.

DEDICATION

To my beloved sons, Ryan and Mitchel and my parents Mr. Seth Okai Ntoni and Madam Augustina Eduah.

ACKNOWLEDGEMENTS

First of all, I am forever grateful to the Almighty God for his divine enablement and guidance throughout my life and the course of my graduate program. He deserves all the Glory and indeed, He has shown me in many ways that "*…in all things God works for the good of those who love Him, who have been called according to His purpose"* (Romans 8:28 NIV).

My next thanks goes to my supervisor, Dr. Henry An, for his support and guidance throughout my research. His comments, suggestions and corrections have honed my research skills and as well made me a better communicator. I am truly grateful.

Furthermore, I would like to thank Dr. Ellen Goddard for her support. Special thanks also go to Genome Canada for funding the study that made possible the data for this thesis. My appreciation also goes to Dr. Getu Hailu and Mr. Xi Yu for making available the data for this study.

Last but not least, I would like to thank my wife, friends and family members who all through their prayers, well-wishes, encouragements and support gave me the strength to complete this thesis. I say, God bless you all and may He provide for you "*…according to the riches of his glory in Christ Jesus"* (Philippians 4:19 NIV).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1 Brief background

The dairy industry is amongst the most highly protected in Canadian agriculture (Schmitz et al. 2010). It operates within a heavily regulated policy environment (i.e., supply management) with combinations of import controls, production quotas and price stabilization arrangements to insulate it from international markets (AAFC 1995; Schmitz et al. 2010). Considering the key role of technology use in the industry (El-Osta and Johnson 1998; El-Osta and Morehart 2000; Schraufnagel 2007; Khanal et al. 2010; Khanal and Gillespie 2013), producers can achieve their profit maximizing objective through the adoption of technologies[1]. Technological change therefore, has been one of the major determinants of structural change in the dairy industry.

Historical data on the Canadian dairy industry suggest smaller farms either expand, merge or exit to create room for more cost-efficient large scale farms (Canadian Dairy Commission 2013). Figure 1.1 presents evidence of this, where a decline in the number of farms corresponds to increases in the average number of dairy cows per farm. Studies looking at the United States' (US) dairy industry – which has experienced similar changes – have attributed these structural changes to the emergence and subsequent adoption of technologies (Khanal et al. 2010; Khanal and Gillespie 2013).

Figure 1.2 also shows how Canada's dairy industry has progressed in terms of productivity gains. Despite all the gains in productivity in the industry, it is still possible

---

[1] The term 'technologies' is used interchangeably with 'innovations' throughout this thesis.

the policy environment in which Canadian dairy producers operate has influenced their technology adoption behaviour. Prasada et al. (2010) for example show how technological change in Canada's supply managed sectors results in increased quota rents rather than increased outputs, exports, consumption and decline in relative supply prices as observed in the other agricultural sectors. Technology adoption is hence crucial and bears the potential to position Canada's dairy industry for international competitiveness among other environmental and societal benefits. That notwithstanding, the decision to adopt a new technology is complex, and in-depth analysis is required to understand producers' adoption behaviour.

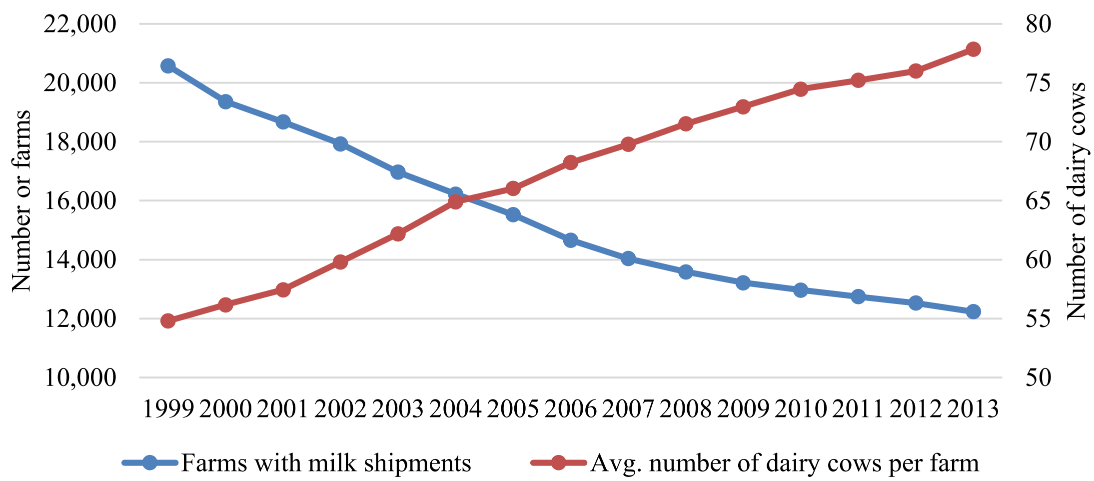


Figure 1.1: Average cows per farm and farms with milk shipments – Canada

Source: AAFC - dairy section, with data from the Canadian Dairy Commission and Statistics Canada

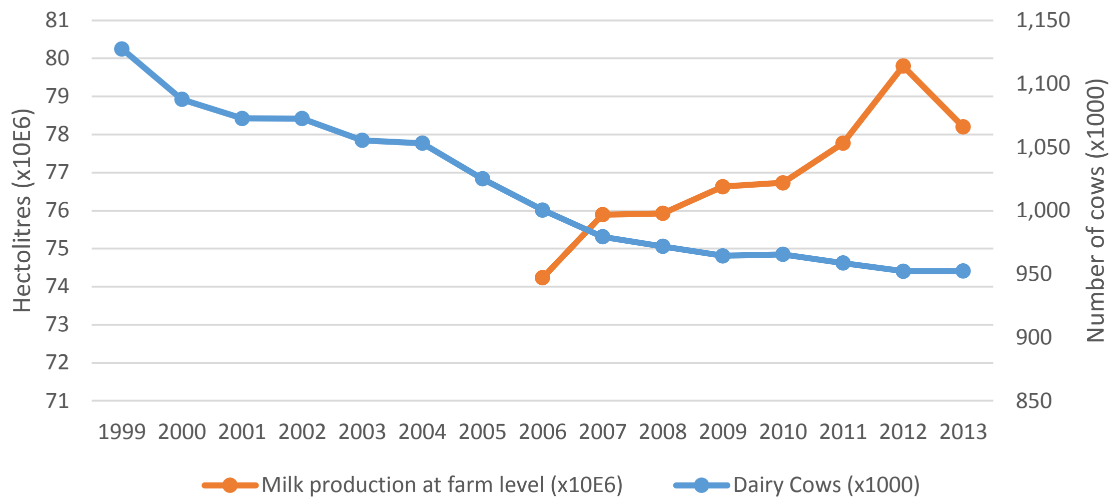


Figure 1.2: Number of dairy cows and milk production at the farm level – Canada

Source: Author; Data from Provincial Milk Boards and Statistics Canada; Calculations by: Canadian Dairy Commission and AAFC - Dairy Section

1.2 Motivation and problem statement

Studies have shown that supply management is associated with inefficiencies such as hindering international trade agreement negotiations; inhibiting gains from economies of scale; welfare transfer from Canadian consumers to producers; and dead-weight losses in the industry (Schmitz 1983; Jeffrey 1992; Richards 1996; Hansen 2013). Proponents of supply management, however, argue that it guarantees stable prices for milk and dairy products when compared with major non-supply managed dairy industries in the world (e.g., US, New Zealand and France) who constantly face price fluctuations (DFC[2] 2014). Also, since dairy producers are considered the economic backbone in rural communities of all Canadian provinces (DFC 2014), the DFC assert that ending supply management will hurt more than benefit the Canadian economy. They bring to attention the need that will

[2] "Dairy Farmers of Canada (DFC) is the national policy, lobbying and promotional organization representing Canada's dairy farmers." - http://www.dairyfarmers.ca/who-we-are/about-us

arise for heavy subsidization with tax payers' dollars as is the case in the European Union (EU) and the US (DFC 2014). Compared to the US and the EU, where the dairy industries are substantially subsidized annually at about $55 billion and $4 billion, respectively, the Canadian industry receives no government subsidies (DFC 2014).

Given Canada's interest in international trade liberalization, supply management as it is currently structured could potentially weaken in the future (Abbassi et al. 2008). For example, the Comprehensive Economic and Trade Agreement (CETA) between Canada and the EU will increase EU's duty-free market access for cheese from 13,000 to 29,800 metric tonnes (Goverment of Canada 2014). Also, the US, Australia and New Zealand are currently demanding that Canada liberate its supply managed sectors (especially dairy) in the on-going negotiations of the Trans-Pacific Partnership (TPP) between Canada and 11 other countries. Although CETA and TPP's impact on supply management could be insignificant (e.g., total cheese production in Canada in 2013 was 407,262 metric tonnes (AAFC 2014)), it appears to be a trend towards greater liberalization. Thus, supply management might eventually weaken or dismantle in the future, and this would consequently expose Canadian dairy producers to international competition.

Therefore, considering the key role of technology in improving productivity and performance in the dairy industry, there is the need to characterize Canadian producers' technology adoption behaviour under the current regime. This among other benefits, will help assess if Canada's dairy industry is well positioned (in terms of technology use) to compete well on the international platform. Some other potential economic benefits to studying producers' adoption behaviour are the implications on the environment and consumers. Through adopting the appropriate technologies, Canadian producers could be as cost-efficient and environmentally friendly as possible. This would imply lower retail prices for milk and milk products as well as lower greenhouse gas emissions from livestock.

To examine Canadian producers' technology adoption behaviour under the current regime, I group 9 dairy technologies into productivity-enhancing (PE) and cost-minimizing (CM) categories. The PE technologies are those whose characteristics emphasize increasing milk yields; whereas CM technologies have characteristics that primarily reduce dairy operational costs. Since dairy producers are less pressured to produce more milk under supply management (Richards 1996), I hypothesize that producers underrate the exigency to adopt PE technologies. This line of thinking has been around for some time now. For instance, Jeffrey (1992) asserted over 20 years ago that if supply management were to end, Canadian dairy producers would not only need to increase their scale of operations, but would also need to increase cow productivity to effectively compete with US dairy producers. Recent annual data on milk yield per cow affirm this disparity as the average US cow yields 10,403 kg per year while the average Canadian cow yields only 9,793 kg (Charlebois and Astray 2012).

Additionally, some studies claim that supply management offers a disincentive for producers to control costs (Goldfarb 2009; Slade 2011). They argue that since the Canadian Dairy Commission (CDC) uses a cost-of-production formula in setting milk price ranges, dairy production is profitable regardless of changing demand or other market conditions (Goldfarb 2009). However, this proposed effect of supply management is unlikely since game theory would require that the producers collude to discourage cost efficiency in order to maintain higher prices. This will be difficult to enforce as well as illegal. The incentive for producers to ‘cheat’ (i.e., be more cost-efficient) is such that the cost-of-production pricing formula should not discourage producers from pursuing CM objectives.

Findings from this study could therefore provide empirical evidence as to whether there is a disincentive for Canadian producers to reduce costs under supply management. Moreover, if my null hypothesis (i.e., there is no difference between producers’ adoption levels of CM versus PE technologies under supply management) is rejected and supply management were to end, we might see a shift not away from CM technologies but towards more PE technologies (Rodenburg 2012). This is because producers’ outputs would no longer be limited by quota, and they would need to compete internationally. Rodenburg (2012) emphatically states that greater efficiency in the Canadian industry will be critical in the future since current trends in international trade agreements will likely pressure the industry to lower prices. The motivation here is to characterize producers’ technology adoption behaviour under the current regime and identify the determinants of adoption of PE and CM technologies. These will help identify possible changes that might be necessary if supply management were to change or weaken; and also understand more about the effects of the system on the types of technologies producers have adopted.

1.3 Objectives

The main goal of this study is to characterize technology use on Ontario dairy farms and empirically estimate the effect of several dairy technologies on cow productivity and farm performance. The specific objectives therefore, are to:

1) calculate adoption levels and characterize farms adopting different dairy technologies;
2) identify the determinants of adoption of PE and CM dairy technologies; and
3) assess the impact of technology adoption on cow productivity and the performance of dairy farms in Ontario.

1.4 Outline of thesis

The remainder of this thesis is organized as follows. Chapter 2 presents a background on Canada's dairy industry with a focus on supply management and its effects on the industry. This chapter also briefly discusses the possible effects of ending dairy supply management in Canada following Australia and New Zealand's example, and concludes with an overview and categorization of key dairy technologies. Chapter 3 reviews the literature on agricultural technology adoption in general and in the dairy industry specifically, with a focus on its impacts on dairy productivity and profitability. Empirical methods used by past studies in analysing technology adoption, cow productivity and performance in the dairy sector are also reviewed. Chapter 4 describes the data and empirical methods used in this study. Results and discussions are presented in Chapter 5 with summary, conclusions and limitations of the study in Chapter 6.

CHAPTER 2: BACKGROUND

This chapter first gives a background on Canada's dairy industry with a focus on supply management and its effects on the industry. A section also briefly talks about the probable effects of the elimination of dairy supply management in Canada using Australia and New Zealand's example. The chapter ultimately concludes with overviews of the dairy technologies under study, their proposed impact on production, and hence, the basis for their categorization.

2.1 Overview of Canada's dairy industry

Canada's dairy industry is of great importance to its economy as it ranks second after red meats in the food and beverages sector[3] (AAFC 2014). Milk and dairy products alone make up about 16% (i.e., $15.7 billion) of the value of manufactured shipments in the food and beverages sector (AAFC 2014). The dairy industry in 2013 comprised 12,234 farms with a total national herd size of about 1.4 million dairy cattle (AAFC 2014). Total milk output was 79.5 million hectolitres (hl) yielding $5.92 billion in total farm receipts for the year (AAFC 2014). According to the Canadian Dairy Information Centre (CDIC), the country supplies over 20% of the world's dairy genetics in the form of cattle, embryo and semen and this contributed more than $122 million to its economy in 2013 (CDIC 2013). The dairy herd in Canada is made of about 94% Holstein; other breeds found on Canadian farms include Ayrshire, Brown Swiss, Canadienne, Guernsey, Jersey and Milking

[3] For comprehensive information and statistics on Canada's dairy industry, refer to the current edition of Agriculture and Agri-Food Canada's publication titled: 'Statistics of the Canadian Dairy Industry' available at http://www.dairyinfo.gc.ca.

Shorthorns (AAFC 2013). About 98% of Canadian dairy farms are family owned and operated (Holstein Canada 2014) and usually have at least 4 enterprises, namely milk production, replacement rearing, cropping and cattle sales for dairy production or beef (Bell 2009).

Focusing on Ontario, agriculture is the second largest sector ($11,952 million) after automotive ($17,635 million) and the dairy industry is the largest (i.e., $1,895 million) in Ontario's agricultural sector (Kulasekera 2013; AAFC 2014; DFO 2014; Staciwa 2014). The Ontario dairy industry is presently made up of about 3,926 farms with 481,900 dairy cattle (CDIC 2014). There are 96 federally and 32 provincially registered dairy processing establishments in Ontario (CDIC 2013a).

Figure 2.1 depicts the size of Ontario's dairy industry, which ranks second in Canada behind Quebec. Together, the two make up 70.41% of Canada's dairy sector. The typical dairy farm in the province has about 85 cows with an average milk yield of 81.52 hl per cow per year (Cairns and Hanmore 2013), compared to the national average of 77 cows with mean output of 78 hl per cow per year (Canadian Dairy Commission 2013).

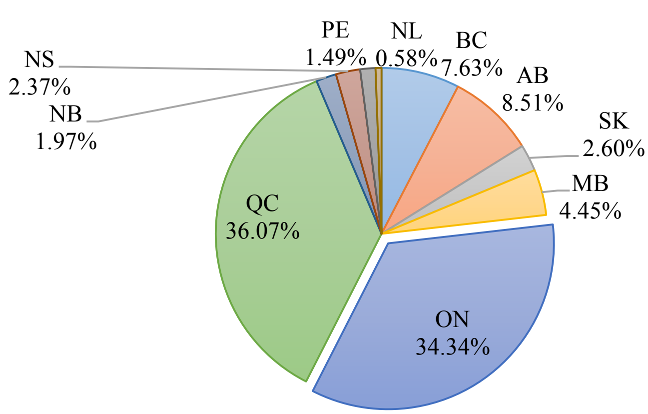


Figure 2.1: Distribution of Canadian dairy herds in 2014 (Total = 1,403,500 cows)
Source: Statistics Canada; calculations done by AAFC-AID, dairy Section

2.1.1 Supply management of the Canadian industry

Supply management of the Canadian dairy industry in its current form started in 1971 (Schmitz 2008). The system was later applied to the poultry (i.e., turkey in 1974 and chicken in 1978) and egg (1973) sectors in Canada as well (Schmitz 2008), and is founded on 3 pillars. The 3 pillars' functions are to: match milk production with consumer demand; acquire fair prices for producers; and keep imports of dairy products at predictable levels (Painter 2007; Goldfarb 2009; DFO 2014). Following is a discussion of how these functions are carried out:

Pillar 1 - Milk price-setting: The Canadian Dairy Commission (CDC) sets the price range to be paid to producers for industrial milk (Schmitz 2008). The target price range set by the CDC is based on several factors including production costs, ultimate use, market conditions, assessment of overall demand for milk and other dairy products and current production levels. The provincial marketing boards, thus, set their own prices based on the CDC's price range. About 40% of Canadian raw milk is sold as table/fluid milk for consumption and the remaining 60% as industrial milk to processors who use it to manufacture other dairy products like cheese, butter, ice cream, milk powder, and yoghurt (Goldfarb 2009). More detailed information on how milk prices are set can be found in (Canadian Dairy Commission 2008). In general, milk price is based on its end use class or components. Under the class system, table/fluid milk and cream receive the highest prices followed by milk sold to processors for the manufacturing of ice cream, yoghurt and sour cream (Canadian Dairy Commission 2008). Following that is milk for making cheese, skim milk powder and butter respectively. Furthermore, milk prices may also vary depending on its actual components like proteins, butter fat, lactose and minerals. Irrespective of the major determining factor of the price-setting mechanism, these are all fixed prices that consumers and processors are forced to pay.

Pillar 2 - Protection from international competition: Since the price-setting mechanism results in prices that are usually higher than what imports of competing products would cost, the Canadian government limits outside competition to maintain its high domestic prices (Goldfarb 2009). The General Agreements on Tariffs and Trades (GATT) in 1993 ruled for import quotas to be replaced with minimum access requirements and tariffs (Schmitz and Schmitz 1994). To that effect, imports in excess of these set limits are exorbitantly taxed (i.e., 168% for eggs, 238% for chicken; 246% for cheese and about 300% for butter) for deterrence (Goldfarb 2009). Moreover, the allowable import quotas are also so small that they have insignificant effects on the domestic market and this effectively shields the domestic industry from international competition.

Pillar 3 - Control of supply: Finally, to prevent overcrowding of dairy producers and the overproduction of milk in the industry, deliberate barriers to entry has been created in terms of production quotas. Each producer is allowed to produce only his/her quota of milk. Upon introduction in 1971, dairy production quota prices have increased from $0 to $28,000 per cow (CDIC 2014). This translates to about $2 million for the average dairy farm and $28 billion nationwide. The high cost of quota has created a major economic distortion in the industry (Goldfarb 2009).

How is supply management implemented in Ontario? - The DFO is the organization responsible for the supply management of Ontario's dairy industry, and it sees to the licensing and administration of quotas (DFO 2014). Essentially, the DFO ensures that all milk quotas owned by dairy producers in the province result in the "collective production of precisely the volume of milk required by processors" (DFO 2014). In addition, the DFO enforce food safety regulations by ensuring producers meet a set of stringent cleanliness, animal health and milk quality standards through farm inspections and regular sample testing in a program referred to as the raw milk quality program (DFO 2014). The DFO is also responsible for milk marketing (DFO 2014) and arranges milk transportation as well as negotiates rates with Ontario's milk transport association. The DFO is also responsible for managing milk quota transfers in Ontario (Chen and Meilke 1998).

2.1.2 Probable effects of deregulation of the Canadian dairy industry

The Australian and New Zealand dairy industries present an appropriate model of the likely effects of deregulating Canada's dairy industry. Australia faced many problems in the process of dismantling its dairy supply management system in 2000. To help farmers make the transition, the government offered tax relief to compensate for losses in quota values and about AUS $1.7 billion transition package to dairy producers (Edwards 2003; Petkantchin 2006). The transition package was funded by a 10 year levy of 11 cents per litre of retail milk. Ending supply management resulted in a decline in farm returns in the first year but farm outputs increased in the following two years after deregulation (Edwards 2003). Hence, farmers who did not exit the industry were forced to be more productive by expanding their herds to benefit from economies of scale and size. Producers who did not expand focused on achieving improved productivity through efficiency in input use. Several ex-post studies (Petkantchin 2006; Government of Australia 2008; Centre for International Economics 2009) conclude that dismantling Australia's dairy supply management has had a positive dynamic effect on productivity, diversification, and the competitiveness of the industry internationally.

Considering Australia’s eventual success in dismantling its supply management system, most researchers have recommended the discontinuation of the system in Canada for both domestic and international trade reasons (Richards 1996; Goldfarb 2009; Hansen 2013; The Conference Board of Canada 2014) by following Australia’s model. They acknowledge the politics behind safeguarding the system but admits the political risks have considerably diminished given the magnitude of the costs of the system and its advocated benefits. The system has been shown to hurt consumers, processors, restaurants, other Canadian enterprises including producers who rely on international trade, as well as dairy producers themselves (The Conference board of Canada 2014).

Likewise for New Zealand, over twenty years after the sudden removal of farm subsidies, a report by the Federated Farmers of New Zealand (2005) entitled “Life after subsidies” firmly establishes how the removal of subsidies has resulted in a more vibrant, diversified and growing rural economy. Their report asserts a growth of about 6% in the economic contribution of the agricultural sector to New Zealand’s economy after subsidies were removed. Despite the predictions of massive de-stocking of herds after the removal of subsidies, New Zealand realized a 49% increase in dairy herd numbers from 1987 to 2004 (Federated Farmers of New Zealand 2005). The report concludes that the removal of subsidies proved to be a catalyst to productivity growth, and that a comparison of the annual growth in productivity gains at the pre (1%) and post (5.9%) periods is a clear indication of the fact. Improvements in productivity at the farm level led to a 33% increase in milk-fat production on average per year from 1987 to 2004. New Zealand now boasts the lowest level of agricultural support (i.e., 2% compared to the OECD average of 31%); and as of 2004, the country held about 30% of the world's market share for dairy product exports. Although Canada's system does not involve direct government subsidies, it involves welfare transfer from Canadian consumers to producers (Schmitz 1983) and as such, it makes no difference if it is direct or indirect subsidisation.

In summary, all the evidence presented by the success of both Australia and New Zealand upon deregulation of their dairy industries indicate Canada is capable of successfully doing the same despite differences in the economic and political settings. There are examples for Canada to learn from and the elimination of supply management in Canada could potentially benefit more than it harms the economy in the long run. Liberalizing the industry is expected to bring about expansion, gains in productivity, diversification, international competiveness and above all consumer welfare benefits. Given the role of technology in modern dairy farming, there are no doubts Canadian dairy producers will need to be at the forefront of dairy innovativeness to survive on a competitive international platform.

2.2 Overviews of the technologies and their categorization

The set of dairy technologies being considered in this study is mainly due to the availability of data. The technologies, however, are mostly state-of-the-art and are currently being rapidly adopted by Canada's major potential international competitors like the EU and US. For example, the adoption of DNA genotyping and breeding technologies (e.g., embryo transfer and artificial insemination) in the US rose from 64.3% in 2000 to 81.5%

in 2005 (Khanal et al. 2010). Hence, I believe the technologies being examined in this study are representative of overall technology use in Ontario and Canada's dairy industry.

Technologies are adopted because the producers think doing so will improve their profitability. Some of them will do so by increasing output per cow, while others will do so by reducing the costs per litre of milk. Thus, the adoption of both productivity-enhancing (PE) and cost-minimizing (CM) technologies are all means to achieving the rational producer's primary objective of maximizing profits. Reilly (1988) used production theory to distinguish between PE and CM technological change. He showed that CM technologies lead to no change in input demand for a given output; whereas PE technologies lead to a reduction in input demand by the technical change factor for a given output. Consequently, Reilly (1988) demonstrated that although output significantly increases in either case (i.e., for both PE and CM technological change), the increase is more with PE than CM technologies. Thus, with Reilly (1988)'s conceptual model in mind, I base my classification of the technologies on their primary benefits to help in identifying it as either a PE or CM technology. The following subsections present brief descriptions of the dairy technologies being studied, their key advantages and/or limitations and the basis for their classification.

2.2.1 Total mixed ration

Total mixed ration (TMR), also known as 'complete ration mix', is a method of feeding cows with weighed and blended feedstuffs (e.g., forages, protein feeds, grains, vitamins, minerals and feed additives) formulated to obtain specific nutrient concentrations in a single feed mix (Linn 2014). TMRs are usually designed by a nutritionist to supply adequate nourishment for the needs of dairy cows to enable them to achieve maximum performance. Hence, a cow upon every bite or mouthful of TMR feed consumes a nutrient-balanced ration. TMR requires cows to be fed in groups (e.g., early, mid-, and late lactation cows) rather than individually and therefore is more suitable for use by producers with large herds (Zheng 2013). Grouping of cows can also be based on reproductive status, age, nutrient requirement and health (Lammers et al. 2003).

The advantages of using a TMR feeding system include: improved feed efficiency, greater accuracy in feed formulation and feeding, flexibility in formulating ration for various cow groups and the benefit of less palatable feed ingredients being masked (Lammers et al. 2003). On the downside, adoption of TMR feeding system comes with moderate to large capital investment and requires regular maintenance of equipment (Linn 2014). Particularly, required feed mixers and proper weighing equipment are usually expensive (Linn 2014). TMR adoption might also require significant structural modifications to existing dairy housing and feeding facilities and therefore can be difficult to implement in some situations (Lammers et al. 2003).

Primarily, TMR adoption results in improvements in cow productivity since proper nutrition is crucial for health and optimal milk production in dairy cows (Linn 2014). VandeHaar and St-Pierre (2006) describe TMR as a PE technology due to its impact on cow nutrition and management. Moreover, they emphasized that TMR is vital to realizing the full genetic potential of high-producing cows. However, they also point out that although good nutrition is crucial for the expression of high genetic potential in dairy cows, TMR confers few benefits for cows with low genetic potential.

2.2.2 Genotyping

Genotyping, also referred to as genomics[4,5] or DNA genotyping, is a process by which differences in the genetic make-up of individuals in species are determined (Kapa Biosystems 2014). This is achieved by examining the DNA sequence of an individual and comparing it with a reference sequence or another individual's sequence. An animal's genomic information can be used in its genetic evaluation and this has revolutionized selection in the dairy industry (Murray 2012). Sequencing of the bovine genome was successfully achieved in 2004 (National Institutes of Health - National Human Genome Research Institute 2004) and has since brought about major advances in breeding and selection in the industry. The use of genomics increases the accuracy of genetic evaluations and has the potential to enhance the rate of genetic improvement in many traits (Murray 2012).

Because most traits are controlled by many genes, genotyping is a complex process and little progress was made until the advent of a genotyping computer chip known as the Illumina 50K test (Murray 2012). Although quite expensive, the 50K test can identify up to 54,609 single nucleotide polymorphisms (SNPs[6]) of value on the bovine genome for selection purposes (Illumina 2014). Cheaper genomic tests kits (i.e., the 3K and 6K) were introduced in 2010 by Holstein Canada and Semex Partners and are now available to Canadian dairy producers for about $47 per animal tested (Murray 2012).

---

[4] The term genome refers to the whole of an organism's hereditary information (Curtis and Grossniklaus 2007)

[5] Genomics is a discipline in genetics that studies the genomes of organisms

[6] An SNP is a location in a chromosome where the DNA sequence can differ by one nucleotide (i.e., Adenine, Thymine, Cytosine, and Guanine) among individuals of the same species (Murray 2012).

Dairy producers usually genotype their cows and heifers to help in identifying superior animals early in life (i.e., shortly after birth) thereby shortening the generation interval in animal selection (Murray 2012). The technology is thus mainly responsible for most of the productivity gains achieved in the industry over the past 50 years. For example, VandeHaar and St-Pierre (2006) attribute the steady rise in US cow productivity in the last century mainly to genetic selection. They emphasize, however, that the modern high-producing cows cannot reach their genetic potential without proper nutrition and management. Genotyping and the use of young genomic bulls for breeding are therefore considered as PE technologies since breeders and producers both use these technologies primarily to select for productivity and performance-enhancing traits in dairy cattle.

Nonetheless, it is worth noting that genotyping also has CM features. Genotyping heifers shortly after birth equips producers with the necessary information to select top replacement heifers for their herd and as well sell excess superior heifers at a premium (Murray 2012). The cost of raising a heifer to 24 months of age is estimated at $2,250 (Murray 2012); thus, the producer can avoid most part of this cost if he can make good culling decisions based on estimated genetic values obtained from genotyping at an early stage.

2.2.3 Robotic milking systems

Robotic milking systems (RMS), also referred to as automatic or voluntary milking systems, are machines (robots) designed to extract milk from dairy animals without human labour (DeLaval 2013). RMS not only extract milk from cows but also have other automated features to control cow traffic during the milking process, clean and disinfect the teats of cows, and collect and store a wide range of data (e.g., production, health and milk-quality) on individual cows (DeLaval 2013). RMS technology became commercially available in the early 1990s and was first introduced in Ontario in 1999 (OMAFRA[7] 2012).

RMS are known to reduce labour requirements on dairy farms significantly, which is the most common reason for adoption them (Rodenburg 2011). However, studies (Kruip et al. 2000; Stockdale 2006; Heikkilä et al. 2010) have found RMS adoption results in higher milk yields per cow as well. This PE effect of RMS adoption is possible since it allows producers to milk their cows more frequently with little additional labour than the usual twice-a-day milking in conventional milking systems (Kruip et al. 2000). Several other studies (Barnes et al. 1990; Campos et al. 1994; J. W. Smith et al. 2002; Wall and McFadden 2008) have also found the positive effect (i.e., up to 20%) of frequent milking (optimally at 3 to 4 times daily) on dairy cow productivity. Therefore, although RMS have the potential of providing CM benefits due to their labour-saving nature, Rotz et al. (2003) argue that this benefit is only realized in the long run since adoption involves extensive capital investment, and a significant period of time is required for the economic benefits to materialize. Hence, the short-to-medium term benefit of adopting RMS is in the area of productivity enhancement rather than cost minimization. I therefore classify RMS as a PE technology in this study.

[7] Ontario Ministry of Agriculture, Food and Rural Affairs

2.2.4 Artificial insemination

Artificial insemination (AI) is a process by which semen with live sperm is collected from the male, processed, stored and artificially introduced into the female reproductive tract for the purpose of conception (Webb 1992). AI bears several advantages over natural breeding, some of which include: provision of a cost-effective means for genetic improvement, prevention and/or elimination of costly venereal diseases (Foote 1996); elimination of the cost and danger of keeping potentially temperamental and dangerous bulls in a dairy herd (Khanal and Gillespie 2013); and better conception rates. Khanal and Gillespie (2013) found that the adoption of AI significantly reduces the cost of milk production. Studies by Hillers et al. (1982), Barber (1983), Seidel Jr (1984), and Olynk and Wolf (2007) have also shown the positive economic benefits of adopting AI. All AI technologies (i.e., AI with sexed semen – AISS; AI with semen from daughter proven bulls – AIDPB; and AI with semen from young bulls - AIYB) among the set being studied are therefore classified as CM technologies.

2.2.5 Dairy herd improvement program

Dairy herd improvement program (DHIP) is a record keeping system set up by an association governed mostly by dairy producers. The association's main purpose is to provide dairy herd management information services and laboratory testing of milk samples for both members and non-members. This information helps sensitize farmers to the multiple aspects of techno-economic performance of their herds and advises on how to manage them to remain profitable and sustainable (Valacta Inc. 2012). DHI services in Canada are offered by CanWest DHI and Valacta.

Adoption of DHIP in the context of this study refers to a producer's enrolment/use of DHI services offered by CanWest[8]. Several authors (Azzam et al. 1989; Cassell 2001; Bewley 2013) have posited that DHIP adoption is a CM strategy for dairy producers. Cassell (2001) for example explains how producers can use information from DHI records to guide culling decisions. He emphasizes how costly it can be for dairy producers to spend feed resources and management skills on unproductive cows, hence the need for profitable culling decisions. Profitable culling decisions requires combing information on production, reproduction, health status, age and other factors; and these information are all made readily available through DHIP (Cassell 2001).

2.2.6 Personal computers

Several authors (Putler and Zilberman 1988; Woodburn et al. 1994; Warren 2002; Tiffin and Tiffin 2005; Tiffin and Balcombe 2011) have stated a variety of farm-level activities that could benefit from the use of personal computers. Generally, dairy producers adopt personal computers to assist them in activities such as record-keeping, planning and production decision-making. The use of computers brings efficiency to most farm operations and therefore turns out to be a resource-saving (e.g., labour and time) technology. Adoption of personal computers is therefore categorized as a CM technology in this study.

---

[8] CanWest provides DHI services for British Columbia, Alberta, Saskatchewan, Manitoba and Ontario whiles Valacta serves Quebec and the Atlantic region of Canada (http://www.canwestdhi.com/company%20profile.htm).

2.3 Summary of categorization of the technologies

Table 2.1 presents a summary of the key technologies, their description and reason for categorization into either PE or CM technology.

Table 2.1: Summary of the key technologies and their categorization

Technology	Category	Description and reason
Total mixed rations (TMR)	PE	A method of feeding cows with weighed and blended feedstuffs specially formulated to obtain specific nutrient concentrations in a single feed mix. Good nutrition primarily boosts cow productivity.
Genotyping (GENO) and the use of young genomic bulls in natural service (YGBNS)	PE	GEON is a process by which differences in the genetic make-up of individuals in species are determined. Producers and breeders use GENO and YGBNS to select for potentially superior (i.e., productive) cows.
Robotic milking systems (RMS)	PE	RMS are designed to extract milk from cows without human labour. RMS also have other automations: e.g., to clean and disinfect the teats of cows. The technology primarily increases cow productivity by allowing cows to be milked more than the conventional twice daily.

Table 2.1 (continued): Summary of the key technologies and their categorization

Technology	Category	Description and reason
Artificial Insemination (AI): - any method - AI with sexed semen (AISS); AI with daughter proven bulls (AIDBP); and AI with semen from young bulls (AIYB)	CM	A process by which semen with live sperm is collected from the male, processed, stored and artificially introduced into the female reproductive tract for the purpose of conception. This saves producers the cost of raising and maintaining bulls and also prevents the spread of costly venereal diseases.
Dairy herd improvement program (DHIP)	CM	DHIP provides dairy management information services and laboratory testing of milk samples. Using DHI services among other benefits provide valuable information for management decisions such as culling. Early culling of unproductive cows can save producers from wasting costly resources.
Personal Computer (PC)	CM	The use of computers to assist in activities such as record-keeping, planning and production decision-making on the farm. The adoption of PCs saves costs through efficiency and resource saving means.

In the next chapter, I review literature on agricultural technology adoption with a focus on the dairy industry. The effect of technology use on the industry is also reviewed along with empirical methods that have been used by researchers in the past to study adoption and its impacts on dairy industries around the world.

CHAPTER 3: LITERATURE REVIEW

This chapter reviews relevant literature on agricultural technology adoption and the factors that influence it. It starts with a review of agricultural technology adoption in general, its basic concepts and theoretical foundations. Following that is a review on technology adoption in the dairy industry with a focus on technology use and its impacts on dairy farm performance. Empirical methods used by past studies in analysing technology adoption, cow productivity and performance of dairy farms are also reviewed.

3.1 Agricultural technology adoption: basic concepts and theoretical foundations

Sunding and Zilberman (2001) present a comprehensive review of the literature on technology adoption and diffusion in agriculture. They describe adoption and diffusion as processes that govern the utilization of innovations. According to them, adoption studies focus on if and when an individual will start to use an innovation. Measures of adoption can either be discrete (i.e., whether or not to use a technology) or continuous (i.e., to what extent or intensity a technology is utilized) (Sunding and Zilberman 2001). Continuous measures of adoption usually apply to divisible technologies like improved crop varieties, fertilizer and the application of herbicides. Adoption of these technologies involve area allocations as well as level of use or rate of application (Sunding and Zilberman 2001). Thus, for divisible technologies, the adoption decision usually involves simultaneously deciding whether to adopt and to what extent/intensity to implement the technology.

Diffusion studies on the other hand measure aggregate adoption and describe how an innovation penetrates its potential market over time (Sunding and Zilberman 2001). Several theories have been used to explain diffusion of innovations. Mansfield (1963) explained diffusion as a process of imitation. According to him, diffusion occurs because of imitation where a farmer's contact with other farmers leads to the spread of the technology. David (1969) used the threshold model to explain diffusion. The threshold model says that there is a cut-off point (threshold) in a particular trait or feature (e.g., farm size, human capital, land quality) beyond which adoption occurs. Thus, diffusion occurs as a particular threshold to adoption declines over time. Rogers (2003) hypothesized that four main elements influence an innovation's diffusion process: the innovation itself, communication channels, time and the population or social system. According to Rogers (2003), how members of a social system perceive the characteristics of an innovation influences its diffusion process. He classified the characteristics of an innovation into: 1) relative advantage, 2) compatibility, 3) complexity, 4) trialability and 5) observability.

As with adoption, there are also several measures of diffusion. Examples include the percentage of a population using a technology over time or the share of total land the technology is being used on (Sunding and Zilberman 2001). Studies have found that technology diffusion follows an S-shaped growth curve (Griliches 1957; Rogers 2003). Rogers (2003) theorized that this S-shaped curve results from the nature of the distribution of adopters over a technology's lifetime. He approximated this distribution to the bell-shaped curve of the normal probability density function and hence, using units of the standard deviation (*sd*) and mean ($\bar{x}$), Rogers (2003) grouped adopters into 5 categories based on when adoption occurs (i.e., their innovativeness); namely: innovators, early adopters, early majority, late majority, and laggards (see **Figure** 3.1).

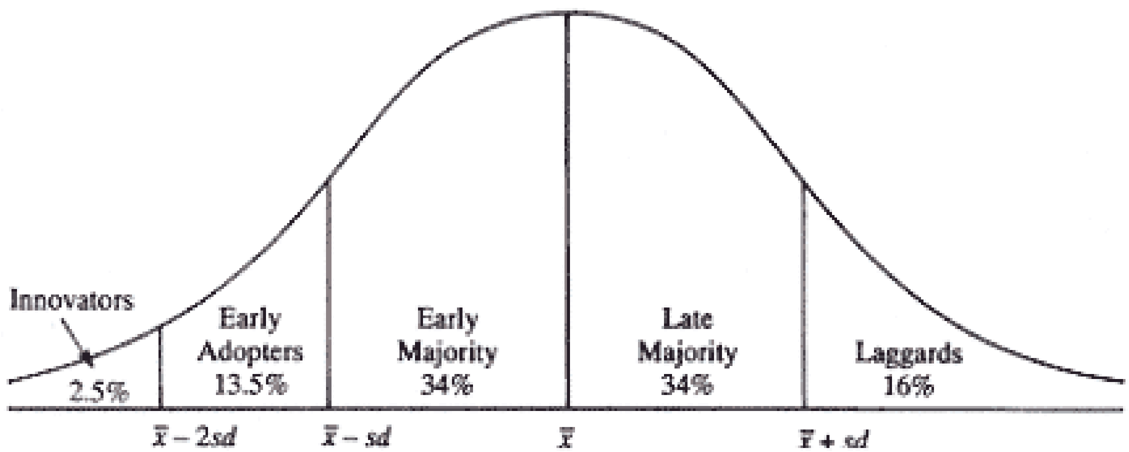


Figure 3.1: Categorization of adopters based on innovativeness
Source: Rogers (2003)

Innovators are the small proportion of farmers who first adopt a technology upon its introduction. Through interaction and association with the first adopters and observing the results of using the technology on their farms, a few more farmers come to know about the innovation and its usefulness and adopt it. This group of adopters are called “early adopters”. They are often younger, more educated and less risk averse. The large number producers of who are observing others’ results in order to make their own adoption decisions are classified as “late adopters”. These farmers are often older, less educated, conservative, and less willing to take risks. After the majority of farmers adopt the innovation, only a few staunch resisters remain who have not adopted the practice. This group of producers is referred to as “laggards”. They are very traditional and take so long to adopt that when they do, another innovation may have already come to replace the previous one. Despite the potential benefits that could accrue from adopting new technologies, there may still be non-adopters and this is usually due to barriers based on factors such as an inability and unwillingness to adopt (Nowak 1992; Rogers 2003).

3.1.1 Determinants of agricultural technology adoption

Since the 1960s, technology adoption and diffusion studies have revolved around three models: the innovation-diffusion model, the economic constraints model, and the technology characteristics-user's context model (Negatu and Parikh 1999). The innovation-diffusion, also known as the transfer-of-technology model, theorizes that access to information about an innovation is a key factor in determining adopters' decision (Rogers 2003). As a result, information flow is a major constraint to diffusion in this model. The model therefore inherently assumes the technology in question is appropriate for use unless otherwise hindered by ineffective communication (Adesina and Zinnah 1993; Negatu and Parikh 1999). The technology characteristics-user's context model is based on the assumption that the characteristics of a technology vis-à-vis users' agro-ecological, institutional and socioeconomic contexts play a key role in the adoption processes (Negatu and Parikh 1999). Finally, the economic constraints model, also known as the factor endowment model, contends that economic constraints, such as access to credit or land, yield, profitability and farm-size significantly affect adoption decisions (Griliches 1957; Mansfield 1963; Sunding and Zilberman 2001).

Several authors (Feder and Umali 1993; Sunding and Zilberman 2001; Rogers 2003) have thoroughly reviewed the literature on the determinants of agricultural technology adoption. Generally, factors that influence agricultural technology adoption are categorized as either social, economic, personal, cultural, institutional (Pannell et al. 2006), as well as factors that relate to the characteristics of the technology (Adesina and Zinnah 1993) or the farm. For example, Prokopy et al. (2008) found producers' access to information, income, farm size, educational attainment, capital, environmental awareness, environmental attitudes and the utilization of social networks as factors that contribute positively to the adoption of best management practices in the US. Sunding and Zilberman (2001) highlighted the role of costs and heterogeneity in terms of factors that relate to the farm's structure (e.g., farm size and land quality) as important in explaining technology on the farm. Producers' human capital characteristics have also been found by many adoption studies as common determinants of adoption (Sunding and Zilberman 2001).

Sunding and Zilberman's (2001) review also showed factors such as producer, farm and technology characteristics, access to information and credit, risk and uncertainty, human capital, land, and market constraints as likely factors that influence adoption. Similarly, Massey et al. (2004) in their survey of the New Zealand dairy industry found the following factors to be important determinants: farm financial stability, debt level, producer innovativeness, education, and age.

It is thus apparent from the brief review of the adoption literature that many explanatory variables are considered important in explaining adoption. With respect to the dairy industry, Khanal and Gillespie (2011; 2013) have found operators' specialization, age and education as important in explaining the adoption of advanced breeding technologies like AI with sexed semen and embryo transplants. Kaaya et al. (2005) found similar factors like producers' age, access to information (in the form of extension visits per year), total farm output and sales, and quality of service as positive determinants of AI adoption in Uganda. Focusing on capital-intensive versus management-intensive technologies, El-Osta and Morehart (2000) identified age, farm size and dairy specialization as positive determinants of the adoption of capital-intensive technologies; while education and size of operation positively influenced the adoption of management-intensive technologies. The choice of explanatory variables used for this study is therefore guided by findings in the literature as well as data availability.

3.2 Technology adoption and its impact on productivity and farm performance

A significant number of studies have established the key role of technology in increasing the productivity and profitability of the dairy industry (El-Osta and Johnson 1998; El-Osta and Morehart 2000; Schraufnagel 2007; Khanal et al. 2010; Khanal and Gillespie 2013). This significant role of technology is not unique to just the dairy industry, but agriculture in general (El-Osta and Morehart 2000; Hennessy and Heanue 2012); and is essential to the survival and international competitiveness of any industry (Tweeten 1992). It is therefore not surprising that findings from different studies (Boehlje 1992; Richards 1996; Gabre-Madhin et al. 2002) have identified technological change as one of the major determinants of structural change alongside factors like financial opportunities, productive human capital and institutional innovations (El-Osta and Morehart 2000). Some other factors that have been identified to improve farm profitability include national and international policies, externalities (Delgado et al. 2008), discussion group memberships (Hennessy and Heanue 2012) and effective extension services (Kilpatrick 1996; Reeve and Black 1998).

Focusing on the dairy industry, advances in genetics, management practices, and technology have greatly contributed to the financial success of producers through gains in productivity and lower per unit production costs (El-Osta and Morehart 2000). This has over the years transformed the structure of the industry and has resulted in consolidation and expansion (Matulich 1978). Historical data affirm this trend in both the US (El-Osta and Morehart 2000; Khanal and Gillespie 2013) and Canadian dairy industries (see Figure 1.1).

El-Osta and Morehart (2000) in their effort to assess the impact of dairy technology use on farms' production performance found that management-intensive technologies positively influence producers' likelihood of being top performers. They also found that adopting capital-intensive technologies could decrease a producer's odds of being a low performer by nearly 16%. In sum, there is a lot of empirical evidence in the literature that firmly establishes the key role of technology adoption in increasing productivity and performance in the dairy industry.

3.3 Empirical methods for analyzing adoption and its impact in the dairy sector

Several studies have discussed and used different econometric methods to study adoption and its impact on the farm (Stefanides and Tauer 1999; Tauer 2001; Foltz and Chang 2002; Fernandez-Cornejo and McBride 2002; Tauer 2006; Ali and Abdulai 2010; Asfaw et al. 2012). Most of the recent technology adoption impact studies with regards to the dairy sector are on recombinant bovine somatotropin (rBST) adoption (Tauer 2001; Foltz and Chang 2002; McBride et al. 2004; Tauer 2005; 2006; Capper et al. 2008) and disadoption (An 2013).

In most cases, adoption models are binary choice (probabilistic) models based on the framework of either random or expected utility theory depending on whether the researcher is interested in analyzing risk. The most common probabilistic choice models are the logit and probit models (and their variants), which are used to model the individual producer's decision to adopt a given technology. Count data models (e.g., Poisson and negative binomial regression) are commonly used if the researcher is interested in the number of technologies in current use on a farm. Contingent valuation methods are also popular in ex-ante adoption studies where researchers seek to estimate willingness-to-pay (WTP) amounts for potential adopters of an upcoming technology.

To assess the impact of technology use on the productivity and performance of a farm, one usually needs to control for the effects of several other factors that may also affect a farm's production and performance. The effects of other technologies and management practices, location and operator characteristics need to be accounted for in order to isolate the effect of a given technology on a farm's productivity or performance measure. There are usually also potential endogeneity and self-selection issues when it comes to adoption impact studies. These are due to the fact the producers are not assigned technologies randomly, but rather decide by themselves whether or not to adopt a given technology. Hence, unobservable factors and characteristics of producers introduce endogeneity into producers' adoption decisions.

Stefanides and Tauer (1999) used a linear regression modeling approach to model the impact of rBST on dairy performance for a sample of 114 dairy farms in New York. With the linear regression framework, they included a technology dummy variable with a set of other regressors to capture the impact of rBST adoption on farm profits. The authors addressed the potential endogeneity of technology adoption by using predicted probabilities from the adoption decision model as an instrumental variable in the adoption impact model. Stefanides and Tauer (1999) were also able to examine both the fixed and random effects specification of their models since they had panel data. Their results show that although rBST adoption was important in increasing milk yield, it had no statistically significant impact on profits. Similarly, Tauer (2001) found virtually the same results of rBST adoption impact on New York dairy farms. Tauer (2001) used probit adoption models with Heckman's two-stage selection and maximum likelihood estimation. Foltz and Chang (2002) and McBride et al. (2004) using probit frameworks and similar corrections for endogeneity and self-selection also found no statistically significant impact of rBST adoption on dairy farm profits.

Tauer (2005) and An (2013) recently used the endogenous switching regression (ESR) approach in estimating the impact of rBST adoption and disadoption, respectively. Tauer (2005) estimated separate switching regressions for rBST adopters and non-adopters and corrected for self-selection bias using probit adoption functions. He found education and herd size as important in explaining adoption and concluded that rBST had no statistically significant impact on per-cow profits. An (2013) also found no statistically significant impact of rBST use on farm profits. However, he showed empirically that current adopters of rBST are doing better than disadopters.

Asfaw et al. (2012) acknowledge the difficulty in conducting adoption impact studies using observational data (i.e., due to potential endogeneity and self-selection issues) and hence suggested and used propensity score matching (PSM) and ESR models. PSM and ESR models address self-selection, but the ESR controls for both observed and unobserved characteristics while the PSM only controls for observed characteristics. They used both PSM and ESR to assess the impact of improved pigeon pea adoption in rural Tanzania and found that adoption significantly boosts household income thereby alleviating poverty. Rosenbaum and Rubin (1983) present a seminal explanation of the PSM procedure and other authors [e.g., Heckman et al. (1997); Dehejia and Wahba (2002); Smith and Todd (2005); and Caliendo and Kopeinig (2008)] have discussed its pros and cons in detail.

Ali and Abdulai (2010) used PSM to assess the impact of adopting *Bacillus thuringiensis* (Bt) cotton on pesticide demands, yields, household income and poverty. They found that the adoption of Bt cotton is significant in increasing yield and income and thus has a poverty alleviating effect. The adoption of Bt cotton also had a significantly negative effect on pesticide use.

Considering the trend in empirical methods used in current adoption and impact studies literature, and the data available; this study uses both PSM and ESR models to examine the impact of productivity-enhancing (PE) technologies on cow productivity. The impact of adoption on dairy farms' cost efficiency is also modeled with PSM and ESR. The ESR model is estimated in addition to the PSM to make use of its major advantage over PSM of controlling for both observed and unobserved characteristics, thus capturing unobserved endogeneity.

CHAPTER 4: DATA AND EMPIRICAL METHODS

This chapter briefly describes the survey method, data and empirical models used for analyses. It starts with a description of the structure of the survey instrument and the sampling procedure used. It then proceeds to describe the data. All empirical models used, their theoretical or conceptual basis and their underlying assumptions are discussed next. Lastly, the expected effects of the explanatory variables used in the models are discussed.

4.1 Data

Data used for this study is from a survey conducted in 2013. The survey was designed to study the use of genomic and other dairy technologies on Ontario dairy farms. It was conducted by students and faculty at the University of Guelph, Ontario with financial support from Genome Canada. The Ontario dairy marketing organization, also known as the Dairy Farmers of Ontario (DFO), randomly selected a total of 2,520 dairy producers who were mailed the survey (Yu 2014). Of these, 205 producers responded, constituting a response rate of 8.1%. Among the 205 observations were different response rates for the various questions of interest with the minimum number of responses being 75, on the cost of producing a hectolitre of milk.

The part of the survey of primary interest to this study asked what technologies among a set of 9 commercially available technologies/management practices were currently being used on the dairy farm[9]. Data on herd size, percent feed costs, producers'

[9] Producers who failed to answer yes/no to the question: 'Do you use any of the following dairy management technologies?' were considered as non-adopters of those technologies.

debt-to-asset ratio, output of milk in the previous year (2012), and ending milk quota holding for the year 2012 were collected. A final section of interest also gathered information on farm and farmer characteristics including producers' educational attainment, sex, years of experience in dairy farming, availability of a successor, dairy and off-farm income percentages and farm ownership.

4.1.1 Multiple imputation

I used multiple imputation (MI) to handle missing observations due to the large number of missing observations in the data set (see Appendix A). For the sample of 205 producers, using the data with missing observations implies case-wise deletion and thus results in 106 complete cases given my logit model specification. Rubin (1987) contend that in such instances, case-wise deletion could result in substantial loss of information and therefore suggests implementing the MI technique to handle missing observations. Using SAS (a statistical software suit), 20 imputations were made for every missing observation with the assumption that the data are missing at random (MAR). Missing at random here means the probability of observing missing observations in a given variable depends on other variables and not the variable itself (Allison 2000). Thus, the variable with missing observations to be imputed is modeled using all the other relevant variables in the data set. SAS uses a Markov Chain Monte Carlo (MCMC) method for the MI procedure, which ensures the resulting data set has a similar distribution as the equilibrium distribution of the original data set (www.support.sas.com). Rubin (1987) confirmed from a simulation analysis that a small number of imputations for a missing observation are adequate when doing MI. He examined the relative efficiency of multiple-imputed data at different levels of percent missingness and concluded that even for data with a high percentage of missing observations, MI is still useful and produces data that yields valid estimates when used for statistical analysis (Rubin 1987).

4.1.2 Descriptive statistics

Descriptive statistics of the data indicate the sample is made of 8.54% females and 90.24% males. 9.76% of the producers are younger than 30 years of age; 38.54% are between 30 and 49 years old and 51.71% are 50 years or over. 47.8% of the producers have secondary education or less, 26.34% have had some form of post-secondary education but not university (e.g., registered apprenticeship or post-secondary diploma), and 25.85% have attended a university for either a certificate, diploma, undergraduate or post-graduate degree (masters or PhD). The typical producer has about 25 years of experience in dairy farming and earns about 84.60% of his household income from dairy operations. Figure 4.1 groups the sample into small (≤50 cows), medium (51-100 cows) and large scale (>100 cows) operations according to herd size. The 3 farm size groups are based on Richards' (1999) categorization. 32.68% of the farms are owner-operated, while partnership and corporation farms constitute 34.15% and 33.17%, respectively. The average number of dairy cows per farm as of December 2012 is 88 cows. The typical farm replaced 5.34% of its cows in 2012. Feed cost constitutes approximately 32.63% of total cost of operation and it cost producers about $38.13 – far lower than the industry average of $56.92 reported by Lang (2013) – to produce a hectolitre of milk. The $38.13 cost per hectolitre of milk includes labour, feed and overhead costs. The representative farm had a debt-to-asset ratio of 29.74% and an ending milk quota holding of 75.8 in 2012.

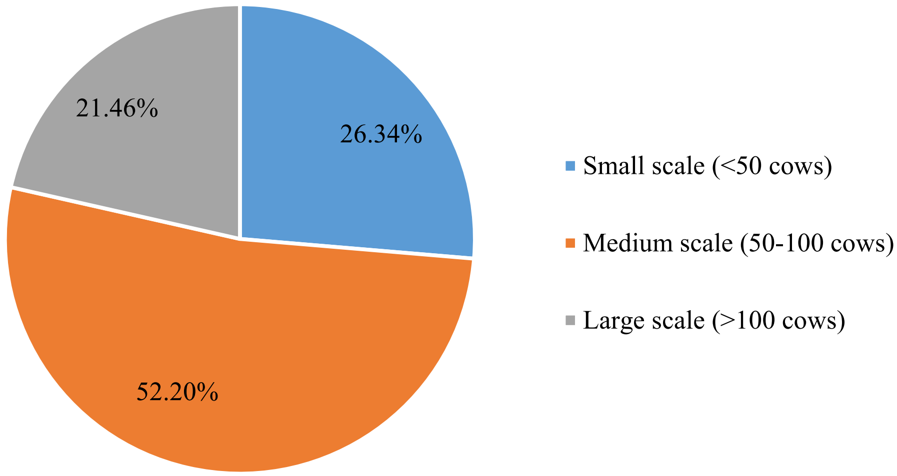


Figure 4.1: Distribution of dairy herd size for respondents (N=205)

Figure 4.2 shows that producers deem production traits (e.g., milk yield, fat, protein) as being the most economically important when deciding to use AI. The traits of least importance to AI adoption decision are associated with fertility. In analyzing factors of importance to producers' decision to use particular semen for AI, quota availability was found to be of least importance while success of previous selection decisions was the most important (Figure 4.3). The importance of the success of prior adoption decisions is consistent with findings from previous studies (e.g., Saha et al. 1994; Klotz and Sana 1995; Grisham and Gillespie 2007). Descriptive statistics for the variables of interest for subsequent analysis are presented in Table 4.1 and 4.2.

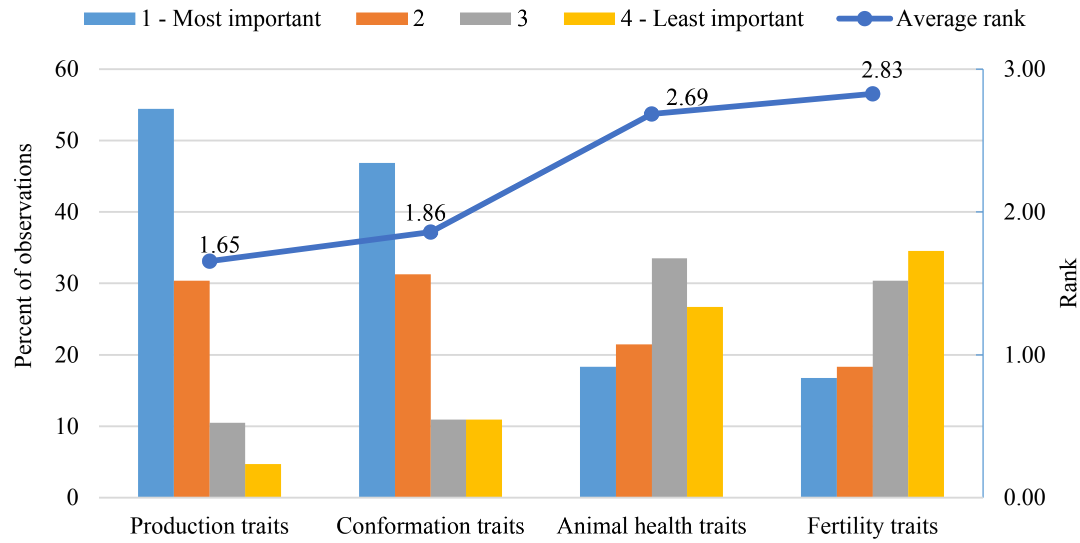


Figure 4.2: Ranking of traits of economic significance to AI adoption

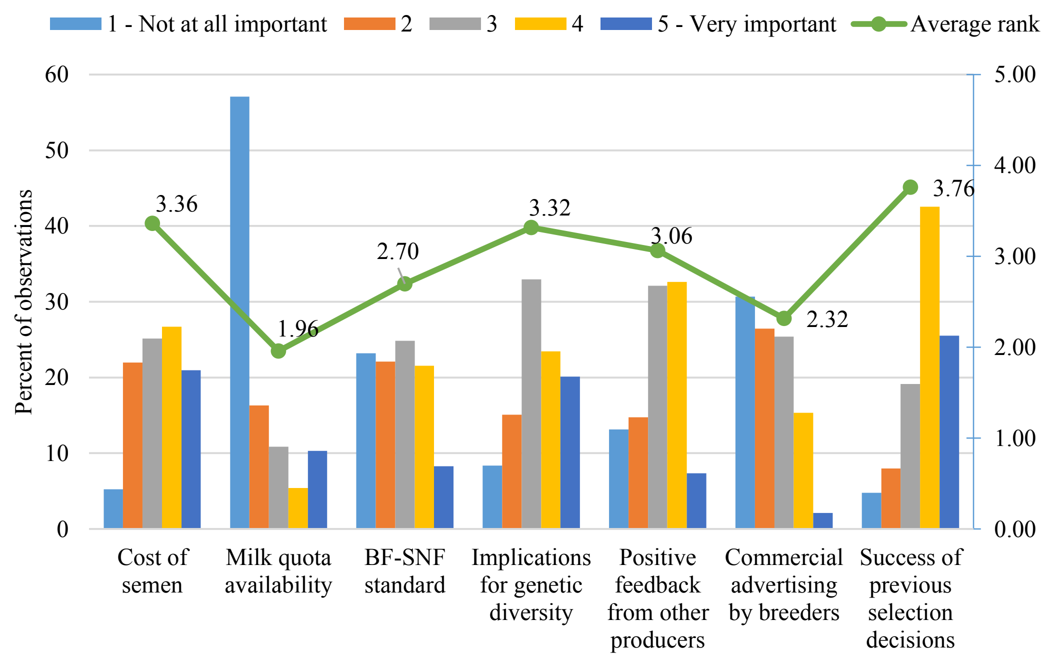


Figure 4.3: Ranking of given factors on decision to use particular semen for AI

Table 4.1: Summary Statistics of variables before multiple imputation

Variable	Units	N	Mean	Std Dev	Min	Max
Post-secondary education	binary	200	0.525	0.5006	0	1
Years of experience	years	200	24.625	14.3009	0	80
Successor	binary	185	0.7135	0.4533	0	1
Planning horizon	years	205	18.0341	13.0009	0	60
Innovativeness	continuous	205	4.9268	1.5433	0	8
Off-farm income	percent	189	49.1111	58.7312	0	90
Dairy herd size	continuous	205	91.2341	121.0212	0	1400
Average annual milk yield	hl/cow	152	110.4452	159.0285	0.5818	912
Percent feed cost	percent	144	32.0486	16.2469	5	80
Debt-to-asset ratio	percent	144	26.8681	23.8786	0	100
Group membership	binary	205	0.6244	0.4855	0	1
Expansion plans	binary	205	0.4537	0.5549	0	1

Table 4.2: Summary Statistics of variables after multiple imputation

Variable	Units	Mean	Std Dev	Min	Max
Post-secondary education	binary	0.522	0.5007	0	1
Years of experience	years	24.5268	14.2501	0	80
Successor	binary	0.722	0.4491	0	1
Planning horizon	years	18.0341	13.0009	0	60
Innovativeness	continuous	4.9268	1.5433	0	8
Off-farm income	percent	11.1	18.0768	0	90
Dairy herd size	continuous	88.3892	78.0276	0	1400
Average annual milk yield	hl/cow	121.272	143.7699	0.5818	912
Percent feed cost	percent	32.318	14.4258	5	80
Debt-to-asset ratio	percent	29.8207	21.8458	0	100
Group membership	binary	0.6244	0.4855	0	1
Expansion plans	binary	0.4829	0.5009	0	1

n=205

4.2 Dependent and Explanatory variables

The dependent variables used in the adoption decision (i.e., binary logit) models are dummy variables that represent yes or no answers to the question of whether or not a producer is currently using a particular technology on his farm. Other dependent variables are productivity and performance measures used for the adoption impact assessment. A farm's productivity is measured by its average annual milk yield whereas performance is measured by share of production cost spent on feed.

Explanatory variables used in the empirical models include the following: primary producer's educational attainment, years of experience in dairy farming, producer's innovativeness (proxied by the total number of technologies in current use on the farm from the set being considered), the existence of a family successor, producer's planning horizon, off-farm income, size of the dairy herd, producer's debt-to-asset ratio and membership in a producer group or organisation. The specific variables and what the literature has found regarding their impact on technology adoption are discussed below.

Post-secondary education

This is a dummy variable that indicates whether or not the producer has attained post-secondary education (post-secondary education = 1 for producers with post-secondary education). Many studies have ascertained a positive effect of education on the probability of adoption (Saha et al 1994; Zepeda 1994; Barrett et al. 2004; Rahelizatovo and Gillespie 2004). The assumption is that producers with higher education are able to easily understand and successfully implement new technologies. Despite the general positive relationship between education and adoption, some studies find the positive effect only for management-intensive technologies and have found no significant effect of education on the adoption of capital intensive technologies (Zepeda 1990; Cardona 1999; Marra et al. 2001).

Size of dairy herd

The dairy herd size variable is a measure of the total number of lactating and dry cows present on the farm. It is an indicator of dairy farm/operation size and is considered an important determinant of adoption. Multiple studies have found a positive relationship between farm/herd size and agricultural technology adoption (Rahm and Huffman 1984; Saha et al.1994; Zepeda 1994; Barham et al. 2004; Gillespie et al. 2004). The reason probably is that large farms are more resourceful (e.g., in terms of credit) and thus can afford the sometimes high fixed costs associated with new technologies. Using the threshold model of adoption, Sunding and Zilberman (2001) explained the existence of a cut-off farm size upon which adoption of a new technology occurs; diffusion therefore occurs over time as the fixed costs associated with the new technology declines.

Dairy experience

The dairy experience variable measures how long (in years) a producer has been in the dairy farming business. It is reasonable to expect producers with more years of experience in dairy farming to be more knowledgeable in the business and thus more careful or hesitant in adopting new technologies. As a result, researchers find both positive and negative relationships and in all cases, the effect is diminishing in experience. Zepeda (1994) for example found a quadratic relationship between farmers' years of experience and the adoption of record keeping practices. This suggests producers find record keeping useful until they become experienced beyond the point where they choose not to use records (Zepeda 1994). Hoag et al. (1999) also found that experience decreases the probability of adoption of a farm computer and this is a common trend in the agricultural technology adoption literature.

Existence of a family successor

The successor variable is a dummy that takes on a value of 1 if the producer has a family member to whom he can pass on the dairy business upon retirement. This variable is expected to increase the likelihood of adoption since having the option of passing on the business to a successor encourages the producer to make long term investment decisions on the farm. Mishra and Williams (2006) found that having a family successor increases the likelihood of internet and computer technology adoption.

Planning horizon

The planning horizon variable measures how many more years the farmer plans on remaining in dairy farming. Studies have found this variable to positively influence technology adoption. The hypothesis is that producers who plan on remaining in the business for a longer period are more likely to invest in technologies that can potentially increase their farm's profitability. Grisham (2007) asserts that having a family successor effectively extends producers' planning horizon thus providing an incentive to carry out long term investments even if the producer does not hope to live long enough to realize the benefits.

Debt-to-asset ratio

This variable is a ratio of the farm's current debts relative to assets. According to Gillespie et al. (2004), debt-free producers are generally considered as either low-input producers or producers who are nearing retirement and thus have little motivation to adopt new technologies. While low or debt-free producers are expected to have greater opportunity for adoption (Gillespie et al. 2004), ex-post analysis of adoption indicate that adopters of capital-intensive technologies have higher debts relative to assets (Gillespie et al. 2004). This is to be expected as the adoption of capital-intensive technologies requires credit to finance and therefore causes adopters to be more indebted. It is no surprise therefore that Feder et al. (1985) in their review found a number of studies that discuss the role of credit constraints in curbing agricultural technology adoption.

Off-farm income

This variable indicates the percent of a farmer's income that is not earned from dairy operations. Feder et al. (1985) found that most studies estimated a positive relationship between off-farm income and the probability of agricultural technology adoption. Their explanation was that working capital is less likely to be constrained if a producer earns off-farm income. Gillespie et al. (2004), however, showed that this is more likely for capital-intensive than management-intensive technologies. Hence, it is expected that the effect of off-farm income on adoption will depend on characteristics of the given technology – that is, whether it is capital- or management-intensive.

Percent feed cost

The percent feed cost variable measures what percentage of the farm's operating costs is spent on feed. Given that feed costs constitute a major component of dairy farms operating costs (Richards 1999), this variable is also considered as a measure for farm performance. The general expectation is that farms with lower percent feed costs (i.e., high performers) in ex-post analysis are more likely to be technology adopters.

Group membership - dummy

This is a dummy variable that takes on a value of 1 if the farmer belongs to a producer group or organisation, other than a dairy herd improvement program (DHIP). It is expected that membership in a producer group will expose the farmer to information and a network of producers. With such a platform, a producer can learn about new technologies in the industry and as well assess the suitability of innovations to his farms. Therefore, the expectation is that the group membership variable will have a positive influence on the likelihood of adoption for most technologies.

4.3 Calculation of adoption levels and characterization of adopting farms

The first objective of this study is to: i) calculate adoption levels, and ii) characterize adopting farms for the various dairy technologies. Adoption levels are calculated across small (≤50 cows), medium (51-100 cows) and large scale (>100 cows) farms. The percentage of adopters for each scale of operation and technology is computed as well as the overall adoption for the whole sample. Average adoption levels for productivity-enhancing (PE) and cost-minimizing (CM) technologies are then compared to determine which category is in high use by Ontario dairy producers. My hypothesis is that producers adopt more CM than PE technologies under supply management.

The second part of objective 1 is to characterize adopters of the various technologies relative to non-adopters. To achieve this, I use the two-sample t-test procedure in SAS. The two-sample t-test is commonly used to test for differences between means or ratios for two groups/samples that are assumed to be independent. Following Cressie and Whitford

(1986), the t-test statistic T for samples assumed to be drawn from populations with a common variance is given by:

$$T = \frac{\bar{X}-\bar{Y}}{\sqrt{\left(\frac{1}{m}+\frac{1}{n}\right)\left(\frac{(m-1)S_X^2+(n-1)S_Y^2}{m+n-2}\right)}}, \tag{4.1}$$

where $X,\ \ i = 1, 2, \dots, m$ are observations for the control group with mean $\bar{X} = \frac{\sum_{i=1}^{m} X_i}{m}$, and variance $S_X^2 = \frac{\sum_{i=1}^{m}(X_i-\bar{X})^2}{m-1}$. The experimental group $Y,\ i = 1, 2, \dots, n$ also has corresponding definitions for $\bar{Y}$ and S_Y^2.

Based on the respective t-test statistics and p-values, I test the hypothesis of whether or not there is a statistically significant difference in characteristics between adopters and non-adopters for a given dairy technology. My approach is similar to that used by Khanal et al. (2010) to study technology adoption in the US dairy industry. It is important to note that the t-test procedure only indicates if there exists a statistically significant difference between the means of specified characteristics of adopters and non-adopters. Hence, it does not test or indicate importance (Studenmund 2005) of these characteristics in explaining adoption.

4.4 Binomial logit adoption model

Objective 2 of this thesis is to identify and estimate the determinants of adoption for PE and CM dairy technologies. To do this, the binomial logit regression model is used. Binomial choice models are used in situations where the outcome variable of interest (i.e., the dependent variable) is not continuous, but binary. Examples include the decision to marry or not, obtain post-graduate education or not, or adopt a new technology or not. The framework for the model pertaining to this study is described below.

Assuming a producer's economic decision to adopt a given dairy technology is based on his net utility of adoption (U_N^*), then $U_N^* = U_A - U_{NA}$, where U_A and U_{NA} are the producer's utility from adopting and not adopting, respectively. Random utility theory suggests a producer will adopt a technology only if $U_A - U_{NA} > 0$. In other words, a producer's net utility from adopting a dairy technology must be positive for adoption to occur.

Producers' utility of adoption is assumed to be a function of farm and farmer characteristics (F), as well as management considerations associated with the technology and the farm (M) (Khanal and Gillespie 2013). Hence, a producer's net benefits from adoption can be written as $U_N^* = f(F, M)$. Representing all variables in F and M by a vector x, and its coefficients by vector β implies:

$$U_N^* = \mathrm{x}'\,\beta + \varepsilon, \tag{4.2}$$

where $\beta = \beta_A - \beta_{NA}$ and $\varepsilon = \varepsilon_A - \varepsilon_{NA}$. The error term ε is assumed to be random and normally distributed. Equation (4.2) is referred to as the linear random utility model (Greene 2003). U_N^* is latent (unobservable), so I cannot actually estimate equation (4.2) because I have no data on utility. However, if I denote adoption by a dummy variable Y, then the underlying condition for observing Y will be given by:

$$Y = \begin{cases} 1 & \text{if } U_N^* > 0 \\ 0 & \text{if } U_N^* \le 0 \end{cases}. \tag{4.3}$$

Thus, a producer's conditional probability of adoption can be written as:

$$\text{Prob}(Y = 1|\text{x}) = \text{Prob}(U_A > U_{NA})$$

$$= \text{Prob}[(\text{x}'\beta_A + \varepsilon_A) - (\text{x}'\beta_{NA} + \varepsilon_{NA}) > 0\ |\text{x}]$$

$$= \text{Prob}[\text{x}'(\beta_A - \beta_{NA}) + \varepsilon_A - \varepsilon_{NA} > 0\ |\text{x}]$$

$$= \text{Prob}(\text{x}'\beta + \varepsilon > 0\ |\text{x}). \tag{4.4}$$

An appropriate model for $\text{x}'\beta$ must satisfy the requirement to produce predictions consistent with the underlying probability theory (Greene 2003). Thus, for a given x:

$$\lim_{\text{x}'\beta \to +\infty} \text{Prob}(\text{Y} = 1|\text{x}) = 1 \quad \text{and} \quad \lim_{\text{x}'\beta \to -\infty} \text{Prob}(\text{Y} = 1|\text{x}) = 0 \tag{4.5}$$

Probability distributions that are commonly used to satisfy conditions in (4.5) include the standard normal and logistic distributions. A probit model is obtained when the standard normal distribution is used; and a logit model when the standard logistic distribution is used. Choosing between probit and logit models is largely a matter of preference since both yield similar results except in their tails. Parameter estimates of a logit model are larger than those of a corresponding probit model by a factor of approximately 1.6 (Cameron and Trivedi 2005; Winkelmann and Boes 2006). In my case, I decide to use the logit model because theory suggests that adoption rates follow an S-shaped logistic curve, which is the basis for the logit model. Based on the logistic function, the logit model is written as:

$$\text{Prob}(Y = 1|\text{x}) = \frac{1}{1 + \exp(-\text{x}'\beta)} = \Lambda(\text{x}'\beta), \tag{4.6}$$

where Λ is the cumulative density function (CDF) of the standard logistic distribution (Greene 2003). With some mathematical manipulation, the logit model can be empirically specified as:

$$\ln\left(\frac{\mathrm{P}}{1-\mathrm{P}}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k, \tag{4.7}$$

where P is the probability of adoption under variable Y and the βs represent parameters of the model to be estimated. The parameter estimates give the impact of changes in the corresponding explanatory variable x_k on the probability or propensity of adoption (Greene 2003). The βs are usually obtained by maximum likelihood methods, which maximize the likelihood of obtaining the data given its parameter estimates (Peng and So 2002). According to Greene (2003), the likelihood function for (4.6) with success probability $\Lambda(x_i'\beta)$ and independent observations is written as:

$$\mathrm{Prob}(Y_1 = y_1, Y_2 = y_2, .., Y_N = y_n | x_i) = \prod_{y_i=0}[1 - \Lambda(x_i'\beta)] \prod_{y_i=0} \Lambda(x_i'\beta), \tag{4.8}$$

Therefore, the likelihood function will be:

$$L(\beta \,|\mathrm{data}) = \prod_{i=1}^{n}[\Lambda(x_i'\beta)]^{y_i}[1 - \Lambda(x_i'\beta)]^{(1-y_i)}. \tag{4.9}$$

Taking logs of (4.9) give the log-likelihood function which is more convenient to work with.

$$\ln L = \sum_{i=1}^{n}\{ y_i \ln \Lambda(x_i'\beta) + (1 - y_i) \ln[1 - \Lambda(x_i'\beta)] \tag{4.10}$$

Statistical software applications such as SAS and STATA usually maximise equation (4.10) or (4.9) with respect to β to obtain estimates of β that maximize the likelihood function.

4.4.1 Estimation of marginal effects and odds ratios for the logit model

A primary objective for modeling with probabilistic choice models like the probit, logit and linear probability models is to compute marginal effect - the effect of a change in an explanatory variable on the conditional probability of an event (i.e., $Y = 1$), *ceteris paribus* (Caudill and Jackson 1989; Cameron and Travedi 2005). Marginal effects are quite useful in econometric applications. In the technology adoption context, marginal effects directly tell how marginal (or discrete - in the case of dummy regressors) changes in explanatory variables affect the conditional probability of adoption. Mathematically, the marginal effect of a continuous regressor is derived by partially differentiating the estimated probability of adoption with respect to the particular regressor.

From equation (4.6), let the density function for the logit model be written as:

$$\frac{d\,\Lambda(x'\beta)}{d(x_i'\beta)} = \frac{exp(x'\beta)}{[1 + exp(x'\beta)]^2} = \Lambda(x'\beta)[1 - \Lambda(x'\beta)]. \tag{4.11}$$

Hence, applying the chain rule of differentiation, the marginal effect for the logit model will be given by:

$$\frac{d\,\Lambda(x_i'\beta)}{d(x_i'\beta)} . \frac{\partial x_i'\beta}{\partial x_i'} = \Lambda(x'\beta)[1 - \Lambda(x'\beta)]\beta. \tag{4.12}$$

Marginal effects for logit and probit models have 3 important characteristics. These are: 1) parameter estimates have the same sign as their corresponding marginal effects; 2) the effect is largest when $x_i'\beta = 0$; and 3) marginal effects vary among individuals in a sample (Greene 2003). For empirical purposes (4.12) is usually evaluated at sample means of x_i or at every data point and the sample mean of the individual marginal effects is calculated. In the case of dummy explanatory variables, the marginal effect is computed as:

$$\text{Prob}[Y = 1 \,|\bar{x}_{(d)}, d = 1] - \text{Prob}[Y = 1 \,|\bar{x}_{(d)}, d = 0], \tag{4.13}$$

where $\bar{x}_{(d)}$ represent means of all the other variables in the model (Greene 2003).

Another intuitive way to present and interpret results from a logit model is to transform the parameter estimates into odds ratios. Given the specification of the logit model in equation (4.7), the dependent variable represents the log of the ratio of the odds of adoption to non-adoption – that is, the log of the odds ratio. Hence, the odds ratio for a regressor can be obtained by exponentiation of the respective parameter estimate (Cameron and Trivedi 2005).

An odds ratio of say 1.5 means a unit increase in the given continuous regressor will increase a producer's odds of adoption by 50%. Likewise, it can also be interpreted as: the odds of adoption are 1.5 times those of non-adoption for every unit increase in the continuous regressor, *ceteris paribus*. Odds ratios for dummy explanatory variables have a similar interpretation. Assuming a dummy indicator of sex (male = 1 and female = 0) has an odds ratio of 1.5, the interpretation will be as follows: the odds of adoption for males are 50% more (or 1.5 times) those for females.

4.5 Adoption impact models

Objective 3 of this thesis is to assess the impact of PE technologies on cow productivity (measured by farms' average annual milk yield) and dairy farm performance (measured by the share of production cost spent on feed). I limit my focus to the impact of just PE technologies because: 1) I assume producers' under the current regime are using adequate CM technologies; and 2) it is all that is needed to ascertain the importance of PE technologies. Thus, evaluating these impacts will help quantify the importance of PE technologies on cow productivity in the industry and performance.

To achieve objective 3, I employ both propensity score matching (PSM) and endogenous switching regression (ESR) methods. Unlike in experimental studies, producers are not randomly assigned technologies. Instead, they make their own adoption decisions based on both observable and unobservable characteristics of themselves and their farms. An example of an unobserved producer characteristic that might simultaneously influence adoption and productivity could be a farmer's management ability. It is possible that high ability farmers are more likely to adopt new technologies and at the same time also likely to be more productive. Hence, adopters and non-adopters might be systematically different. This self-selection makes it difficult to do an ex-post assessment of the impact of adoption on an outcome variable using observational data (Asfaw et al. 2012).

In light of the econometric problem afore mentioned, both the PSM and ESR methods are econometrically appropriate to handle the potential self-selection issue that characterizes technology adoption. PSM, however, only controls for observable characteristics whereas ESR accounts for both observable and unobservable characteristics. Next is a discussion of the two techniques and how they are implemented.

4.5.1 Propensity score matching model

First published by Rosenbaum and Rubin (1983), the rationale behind the technique is to estimate among a sample of treated and untreated individuals, the effect of receiving treatment. The technique creates statistically comparable groups by matching observations in a treated group to those in a control group with similar characteristics to estimate the effect of receiving treatment. In other words, the PSM technique allows for identification of a causal link between treatment and an outcome variable such as cow productivity or percent feed cost. Using PSM for adoption impact analysis mimics an experimental set-up in which a technology is assigned randomly thereby eliminating selection bias (Caliendo and Kopeinig 2008; Asfaw et al. 2012). Numerous studies have used PSM in the past to evaluate the impact of technology adoption, and some of these are: Kijima et al. (2008) González et al. (2009); Mayen et al. (2010); Kassie et al. (2011); Asfaw et al. (2012) and Rao et al. (2012).

In this thesis, PSM is used to assess the impact of PE dairy technologies on milk yield and farm performance. Adopters of a technology are referred to as the treated group, and non-adopters are the control/untreated group. Following Heckman et al. (1997) and Asfaw et al. (2012), the PSM technique is implemented in two stages. First, a probabilistic model (logit model) as described in section 4.4 is used to predict the conditional probabilities (propensity scores) of adoption given a set of pre-treatment characteristics x as shown in equation (4.14).

$$p(x) = \text{Prob}\ (D = 1 \mid x) = E(D \mid x), \tag{4.14}$$

where $p(x)$ represents the propensity scores from the logit model and D is a dummy for adoption.

The second step involves matching observations from the treated and control groups based on their propensity scores. Since propensity scores are conditioned on producer's observed characteristics, matching based on the scores ensures that every observation in the control group is matched to a similar individual in the treated group. This enables establishment of the counterfactual situation and also allows us to evaluate the average treatment effect on the treated (ATT); in other words, the average impact of adoption on the adopters. Mathematically, ATT can be expressed as:

$$\text{ATT} = E(Y_1 - Y_0 \mid D = 1) = E(Y_1 \mid D = 1) - E(Y_0 \mid D = 1), \tag{4.15}$$

where, $E(Y_0 \mid D = 1)$ represents the unobservable counterfactual that needs to be estimated. The ATT in this case assesses the impact of adoption by measuring the average difference in cow productivity (or percent feed cost) between adopters and a counterfactual situation of adopters had they not adopted.

The most popular methods in the literature for matching the propensity scores are: nearest neighbour, radius, stratification and kernel matching methods. With nearest neighbour matching, every treated observation i is matched with the closest control observation j based on their propensity scores p_i and p_j (Caliendo and Kopeinig 2008; Grilli and Rampichini 2011). Hence, nearest neighbour matching is determined by min $|p_i - p_j|$ and can be done with or without replacement. When a control observation is used only once in matching, it is referred to as matching without replacement otherwise it is with replacement (Caliendo and Kopeinig 2008; Grilli and Rampichini 2011). The radius (also referred to as calliper) matching method matches each treated observation i with control observations j that fall within a specified radius r. Thus, radius matching ensures $|p_i - p_j| < r$. This eliminates the possibility of bad and too distant matches (Caliendo and Kopeinig 2008). Stratification or interval matching method divides the common support area of treated and control groups into sections called strata. The effect of each section is computed by comparing the outcomes within strata of propensity scores

(Caliendo and Kopeinig 2008). Finally, in kernel matching (also known as local linear matching) each treated observation i is matched with all control observations j by weight w. Every observation's weight is inversely proportional to the distance between treated and control observations thus ensuring more distant observations have lesser weights. A distinguishing feature of the kernel matching method therefore is that all observations in the control group are used in every match made. For comparison purposes, I will use all the 4 popular matching methods descried.

After successfully matching the propensity scores, the next step is to estimate the treatment effects. Let Y_1 and Y_0 represent a producer's two possible outcomes for milk yield (or percent feed cost). The producer's milk yield is Y_1 if he is an adopter and Y_0 if he is a non-adopter. Note that only one of these outcomes can be observed depending on the producer's decision to adopt or not. The effect/gains of adopting a given technology on a producer's milk yield is given by $\Delta = Y_1 - Y_0$. Since gains from adoption will typically be different across individuals, a standard approach is to measure these gains for a group of individuals (Verbeek 2004). Thus, we calculate the average treatment effect (ATE) as shown below:

$$\text{ATE} = E(Y_1 - Y_0) = E(Y_1 \mid x, D = 1) - E(Y_0 \mid x, D = 0). \tag{4.16}$$

ATE measures the average effect, at the population level, of non-adopters becoming adopters whereas ATT measures the average effect of adoption on adopters. (Austin 2011). However, the ATE is only appropriate in experiments where treatment is randomly assigned; but in observational studies, the ATE may be biased if the treated and control observations are not similar (Caliendo and Kopeinig 2008). Hence, the most commonly used measure in the PSM literature is ATT.

After matching on propensity scores and satisfying underlying assumptions (Caliendo and Kopeinig 2008), the PSM estimator for ATT can generally be written as:

$$\mathrm{ATT} = E(\Delta \mid p(x), D = 1) = E(Y_1 \mid p(x), D = 1) - E(Y_0 \mid p(x), D = 0), \tag{4.17}$$

where $E(Y_0 \mid p(x), D = 0)$ is used as an approximation for $E(Y_0 \mid D = 1)$, – that is the counterfactual in equation (4.15).

Some assumptions necessary to enable estimation of ATT as specified in (4.17) include: the balancing assumption and the conditional independence assumption (CIA) also known as the unconfoundedness assumption (Rosenbaum and Rubin 1983). Balancing is a testable assumption that ensures that given the same propensity score, assignment to treatment is independent of producers' characteristics. The balancing condition is mathematically denoted as: $D \perp x \mid p(x)$ and suggests adoption is independent of producer and farm characteristics, given the same propensity score (Katchova 2013). The CIA also assumes potential outcomes are independent of treatment assignment given a set of observable covariates, which are unaffected by the treatment (Caliendo and Kopeinig 2008). Also It is mathematically expressed as: $Y_0, Y_1 \perp D \mid x$. The CIA assumption ensures that the decision to adopt is random conditional on observed covariates (Asfaw et al. 2012). Also, there is the region of common support condition which ensures any bias that may result from non-overlapping supports is removed by matching only over the region of common support (Heckman et al. 1997).

4.5.2 Endogenous switching regression model

The ESR model is a simultaneous equations model made up of a selection equation (i.e., the technology adoption model) and two outcome (i.e., productivity/percent feed cost outcomes) equations. Following Lokshin and Sajaia (2004); Di Falco et al. (2011); and Asfaw et al. (2012) consider a model that describes the outcome of a dairy producer with two regression equations and a selection function D^* that determines which regime (i.e. adoption or non-adoption) the producer belongs to:

$$D^* = \beta X + u \text{ with } D = \begin{cases} 1 \; if \; D^* > 0 \\ 0 \; otherwise \end{cases}, \quad (4.18)$$

$$\text{Regime 1:} \quad Y_1 = \alpha_1 J_1 + e_1 \quad if\, D = 1, \quad (4.19a)$$

$$\text{Regime 2:} \quad Y_2 = \alpha_2 J_2 + e_2 \quad if\, D = 0, \quad (4.19b)$$

where D^* is the net utility from the decision to adopt a certain technology or not, D is the observable adoption decision (so $D = 1$ for adoption and 0 for non-adoption), X is a vector of observed farm and non-farm characteristics that influence the adoption decision, Y_1 and Y_2 represent cow productivity outcomes in regimes 1 and 2, respectively, J represents a vector of exogenous variables that influences cow productivity, and u and e_i, $i = 1,2$ are random error terms associated with the adoption and productivity equations, respectively.

The usual order condition of X containing at least one variable not present in J helps impose an exclusion restriction to enable identification in the model (Lokshin and Sajaia 2004). A general requirement is that such selection instruments must be important in explaining adoption but not productivity (or performance). Also, the error terms are assumed to have a trivariate normal distribution with zero mean and a non-singular covariance matrix given by:

$$\operatorname{cov}(u, e_1, e_2) = \begin{pmatrix} \sigma_u^2 & \sigma_{e1u} & \sigma_{e2u} \\ \sigma_{e1u} & \sigma_{e1}^2 & . \\ \sigma_{e2u} & . & \sigma_{e2}^2 \end{pmatrix} \tag{4.20}$$

where σ_u^2 is the variance of the error term in the selection equation (4.18), which can be assumed to be equal to 1 since β is estimable only up to a scalar factor. σ_{e1}^2 and σ_{e2}^2 are variances of the error terms in the respective outcome equations. σ_{e1u} and σ_{e2u} are covariances of the respective outcome equations (i.e., (4.19a and 4.19b) and the selection equation (4.18). It is important to note that the covariance between the two outcome equations is undefined since it is impossible to observe both regimes simultaneously. An important implication of the error structure of the ESR model is that the expected values of e_1 and e_2 conditional on the adoption (selection) equation are non-zero (Asfaw et al. 2012). Thus:

$$E[e_1|D = 1] = \sigma_{e1u}\lambda_1 \text{ and } E[e_2|D = 0] = \sigma_{e2u}\lambda_2$$

where $\lambda_1 = \frac{\phi(\beta X)}{\Phi(\beta X)}$ and $\lambda_2 = -\frac{\phi(\beta X)}{1-\Phi(\beta X)}$. $\phi(.)$ and $\Phi(.)$ represent the standard normal probability and cumulative density functions, respectively.

To estimate the ESR model, it is considered efficient to use the full information maximum likelihood (FIML) estimation method (Lokshin and Sajaia 2004; Di Falco et al. 2011). The FIML method simultaneously fits the binary [i.e., (4.18)] and continuous parts [i.e., (i.e., 4.19a and 4.19b)] of the model to yield consistent standard errors (Lokshin and Sajaia 2004; Asfaw et al. 2012). Given the assumption with respect to the distribution of the error terms, the log likelihood function for the system of equations is given as:

$$\ln L = \sum_{i-1}^{N} D\left[\ln\phi\left(\frac{e_1}{\sigma_{e1}}\right) - \ln\sigma_{e1} + \ln\Phi(\varphi_1)\right]$$

$$+ (1-D)\left[\ln\phi\left(\frac{e_2}{\sigma_{e2}}\right) - \ln\sigma_{e2} + \ln(1-\Phi(\varphi_2))\right] \quad (4.21)$$

where $\varphi_{ji} = \frac{(\beta X + \gamma_j e_j/\sigma_j)}{\sqrt{1-\gamma_j^2}}, ji = 1, 2.$ γ_j represents the correlation coefficient between u and e_1 and e_2, respectively.

Once the parameters of the model have been estimated, the following conditional expectations can be calculated to enable assessment of the impact of adoption:

$$E(Y_1|D = 1) = \alpha_1 J_1 + \sigma_{e1u}\lambda_1 \quad (4.22a)$$

$$E(Y_2|D = 0) = \alpha_2 J_2 + \sigma_{e2u}\lambda_2 \quad (4.22b)$$

$$E(Y_2|D = 1) = \alpha_2 J_2 + \sigma_{e2u}\lambda_1 \quad (4.22c)$$

$$E(Y_1|D = 0) = \alpha_1 J_1 + \sigma_{e1u}\lambda_2 \quad (4.22d)$$

Equations (4.22a) and (4.22b) present the expected productivity (or performance) outcomes of actual adopters and non-adopters respectively while (4.22c) explores the expected productivity (or performance) outcomes in the counterfactual hypothetical cases for adopters had they not adopted; and (4.22d) for non-adopters if they had adopted (Di Falco et al. 2011). Therefore, following Di Falco et al. (2011) and Heckman et al. (2001), two measures of the impact of adoption can be computed from (4.22a-d) as follows: i) The impact of adoption on adopters (i.e., the effect of treatment on the treated - TT) and ii) the supposed impact of adoption on non-adopters if they had adopted the technology (i.e., the effect of treatment on the untreated - TU).

$$\mathrm{TT} = E(Y_1|D = 1) - E(Y_2|D = 1) = J_1(\alpha_1 - \alpha_2) + \lambda_1(\sigma_{e1u} - \sigma_{e2u}), \text{ and} \tag{4.23}$$

$$\mathrm{TU} = E(Y_1|D = 0) - E(Y_2|D = 0) = J_2(\alpha_1 - \alpha_2) + \lambda_2(\sigma_{e1u} - \sigma_{e2u}). \tag{4.24}$$

4.6 Diagnostic and statistical testing

Explanatory variables included in the models were tested for their statistical significance at the 10% level. In addition to statistical significance testing, diagnostics for other potential econometric problems like collinearity and heteroskedasticity that were conducted are discussed below.

Collinearity or multicollinearity results when there is a strong linear relationship between two or more explanatory variables in a model such that it can significantly affect estimation of the parameters of the model (Studenmund 2005). Collinearity increases standard errors and therefore reduces the significance of estimated parameters. The existence of collinearity can conceal the actual relationships between data (Studenmund 2005). Due to increased variances, collinearity might also be responsible for unexpected signs on the affected parameters (Studenmund 2005). This is because the distribution of the estimated parameters becomes wider with collinearity than without it.

To detect collinearity, I created a correlation matrix using all of the regressors in the models and the rank option in SAS to help rank all the Pearson correlation coefficients (r) in an order of decreasing absolute magnitude. Upon a visual inspection of the matrix, all variable-pairs with |r| greater than 0.80 as suggested by Hill et al. (2001) and

Studenmund (2005) were considered collinear and hence, further scrutinized. Upon detection of collinearity, further examination is made to determine if the highly correlated variables are redundant on not according to the literature and logical reasoning. It is good to exclude a redundant variable from a regression model, but one must be careful not to exclude a non-redundant variable since this might lead to more serious econometric problems such as omitted variable bias or model specification errors (Studenmund 2005). Therefore, unless the correlated variables can be considered redundant, it is commonly safe to do nothing about collinearity problems.

Upon examining the results from the correlation matrix, I found producer age to be highly correlated with planning horizon (r = -0.825) and years of experience in dairy farming (r = 0.822). Also, dairy herd-size was highly correlated with producer's quota holdings (r = 0.983). Hence, I excluded producer age and quota-holdings from my regression models since they are redundant to their highly correlated counterparts.

Another way to detect collinearity is to compute the variance inflation factor (VIF) for each regressor included in the model. $VIF = (1 - R^2)^{-1}$, where R^2 refers to the unadjusted R^2 from regressing each independent variable on all of the remaining independent variables (Studenmund 2005). Although there's no formal table of critical VIF values to indicate collinearity, VIFs greater than 5 or 10, depending on the number of regressors used in the model are generally considered high enough to cause severe collinearity problems (O'Brien 2007).

Heteroskedasticity is a violation of classical assumption 5 of the linear regression model. This assumption requires observations of the error term to be drawn from a distribution with constant variance (Studenmund 2005). In other words, existence of heteroskedasticity causes the probability density function to be more spread out compared with homoskedastic errors (Hill et al. 2001; Studenmund 2005). A parameter estimate of a heteroskedastic model is unbiased but can no longer be considered to be the best linear unbiased estimator of the coefficients because standard errors are inflated. Consequently, hypothesis testing and confidence intervals based on them can be misleading (Hill et al. 2001; Studenmund 2005).

Since heteroskedasticity is a common problem with cross-sectional data, I conducted model post-estimation diagnostics on the models to assess whether the errors were heteroskedastic. First, I plotted the residuals of the estimated models with all included continuous regressors and then visually inspected the plots for non-random relationships (Hill et al. 2001). The Breusch-Pagan (B-P) test procedure can also be sued to determine the likelihood of heteroskedasticity in a model. The null hypothesis for the B-P test is that the variances of the residuals are constant (or homoskedastic) and the alternative hypothesis is that variances of the residuals are heteroskedastic. The null hypothesis of heteroskedasticity is rejected if the p-value of the B-P test statistic is less than 0.10. Due to the existence of heteroskedasticity in some of my models, I estimate them with robust standard errors to account for heteroskedasticity.

CHAPTER 5: RESULTS AND DISCUSSIONS

5.1 Introduction

This chapter presents the empirical results and a discussion of the findings. Each specific objective of this thesis is examined, and the results are presented in the following order:

1. results of adoption levels and characterization of adopting farms;
2. determinants of adoption of the dairy technologies; and
3. impact of adoption of productivity-enhancing (PE) technologies on cow productivity and dairy farm performance.

5.1.1 Adoption levels of PE and CM dairy technologies

Results from Table 5.1 reveal a positive relationship between farm size and the adoption of dairy technologies. In general, large farms have the highest average adoption levels while small farms have the least for both PE and cost-minimizing (CM) technologies. An equality of means test showed that the differences in adoption levels are statistically significant at the 99% confidence level for all corresponding farm-size groups in the PE and CM categories. AI with semen from daughter proven bulls (AIDPB) is the most adopted technology among the set, while robotic milking systems (RMS) have the lowest overall adoption level. The results generally support the hypothesis that Canadian dairy producers are more inclined toward adoption of CM technologies (76.10%) than PE technologies (28.05%). The observed trend in dairy technology adoption is likely a consequence of supply management. This is because under supply management, a producer's milk output is subject to quota restraints, but his cost-minimization efforts are not. Hence, producers would consider it more attractive to directly pursue CM objectives rather than seek enhancements in cow productivity. Another reason for the observed high adoption levels of CM technologies could also be because producers who are more cost-efficient stand to benefit most from the cost-of-production pricing formula used by the Canadian Dairy Commission (CDC).

Table 5.1: Adoption levels for PE and CM dairy technologies

Technology	Adoption level (%) by herd size: Small scale (≤50 cows) (n = 54)	Medium (51-100 cows) (n = 107)	Large scale (>100 cows) (n = 44)	Overall adoption (n = 205)
Productivity-enhancing technologies				
Total mixed rations (TMR)	48.15	80.37	88.64	73.66
Genotyping (GENO)	12.96	25.23	18.18	20.49
Young genomic bull in natural service (YGBNS)	5.56	11.21	18.18	11.22
Robotic milking systems (RMS)	5.56	6.54	9.09	6.83
Average PE	**18.06**	**30.84**	**33.52**	**28.05**
Cost-minimizing technologies				
AI with semen from daughter proven bulls (AIDPB)	87.04	92.52	88.64	90.24
Milk recording (DHIP)	75.93	91.59	93.18	87.80
AI from young bulls (AIYB)	81.48	87.85	84.09	85.37
Personal computer (PC)	53.70	79.44	86.36	74.15
AI with sexed semen (AISS)	35.19	42.06	54.55	42.93
Average CM	**66.67**	**78.69**	**81.36**	**76.10**
Mean Difference (PE – CM)	*-48.61****	*-47.85****	*-47.84****	*-48.05****
t-value	-14.5103	-20.222	-10.589	-26.816

*** $p<0.01$

The t-values measure if there is any statistically significant difference between the average adoption levels of PE and CM technologies.

5.1.2 Characterization of adopting farms

The results from the two-group mean-comparison tests describe how producers differ in terms of a wide range of producer and farm characteristics. I tested for differences in the same set of producer and farm characteristics across adopters and non-adopters of all 9 technologies. However, Table 5.2 and Table 5.3 only present those characteristics that have statistically significant differences between adopters and non-adopters of the respective technologies.

Results from Table 5.2 on total mixed rations (TMR) adoption corroborate the known benefits and expected characteristics of TMR and its potential adopters. As anticipated, the findings suggest adopters of TMR operate larger farms compared with non-adopters. This supports the fundamental idea of TMR feeding: that cows be grouped (e.g., by lactation cycle, reproductive status, age, nutrient requirement and health) so that they can be fed the right blend of nutrients for optimal performance and productivity (Linn 2014). Group feeding is more practical and cost effective for farms with large herds. Table 5.2 also suggests adopters of TMR have higher debt-to-asset ratios, which indicates the substantial capital investment required for adoption of the technology.

Other characteristics of TMR adopters according to the results are: superior innovativeness (i.e., they adopt more of the other technologies on the aggregate), higher off-farm income and greater likelihood of belonging to a producer group. Another important result is that adopters of TMR are more likely to have a successor upon retirement. This meets expectations since plans for passing on the farm business to a successor provide producers with more incentive to undertake important capital investments on the farm, even if they do not live long enough to realize its full benefits (Grisham 2007).

On DNA genotyping (GENO), the results (see Table 5.2) suggest GENO adopters spend relatively less on feed compared with non-adopters. This corroborates the discussion earlier in section 2.2.2 that GENO adoption could possibly have both CM and PE benefits. Table 2.1 also suggests that GENO adopters are generally more educated, more innovative and also more likely to belong to producer groups. Table 5.2 indicates that adopters of GENO technologies have plans to expand their dairy farms within the next 5 years but cite quota limitations as a major constraint.

All these characteristics conform to expectations given the nature and benefits of GENO adoption as discussed in section 2.2.2.

From the results, adopters of young genomic bulls for natural service (YGBNS) are mostly large-scale dairy producers. This suggests YGBNS adoption might be an unsuitable or uneconomical option for small- and medium-scale dairy farms as they might not have the right facilities to accommodate and maintain bulls on their farms. This is possibly because bulls are usually more vicious and require expertise in their handling (Khanal et al. 2010). Non-adopters of YGBNS, however, have higher education and on average interact more with other producers in a given month compared to adopters. TMR and DHIP were the other technologies whose adopters were characterized by more interactions with other producers in a given month.

Finally, the results in Table 5.2 suggest that adopters of robotic milking systems (RMS) are more innovative and more likely to belong to a producer group. Unexpectedly, however, RMS adopters have significantly lower average milk yields per year compared to non-adopters. One would expect otherwise since RMS adoption enables producers to milk more frequently (3-4 times a day), which has been shown to increase milk yield in lactating cows (Barnes et al. 1990; Campos et al. 1994; Smith et al. 2002; Wall and McFadden 2008). This unexpected result could possibly be due to the extremely low overall adoption level (6.83% of 205 producers) observed in the sample, and the possibility that adopters of RMS are generally "lower performers" who are using RMS to improve their low yields.

Table 5.2: Characteristics of PE technology adopters

Productivity-enhancing technologies	Adopters	Non-adopters	|t-value|	Prob>t
Total mixed rations				
Debt-to-asset ratio	30.21	15.30	3.50	0.0006***
Dairy herd size	93.79	57.04	4.91	0.0001***
Future extension	0.56	0.28	3.06	0.0025***
Group membership	0.69	0.44	3.25	0.0014***
Innovativeness	5.46	3.44	8.93	0.0001***
Off-farm income	8.92	5.20	1.75	0.0821*
Farm ownership type	2.08	1.80	2.09	0.0379**
Quota	82.30	37.99	5.71	0.0001***
Social interaction	3.98	2.37	2.78	0.0063***
Succession	0.75	0.62	1.72	0.0878*
DNA genotyping				
Percent feed cost	27.32	33.19	2.37	0.0204**
Future extension	0.63	0.45	1.79	0.0743*
Group membership	0.81	0.58	3.21	0.0019***
Innovativeness	6.36	4.56	9.97	0.0001***
Post-sec. Education	0.67	0.47	2.26	0.0247**
Quota limitation	2.93	2.46	1.70	0.0903*
Young genomic bulls in natural service				
Dairy herd size	116.70	79.99	1.72	0.0982*
Post-sec. Education	0.35	0.53	1.71	0.0978*
Social interaction	2.15	3.73	2.28	0.0306**
Robotic milking systems				
Avg. Annual milk yield	78.23	112.20	2.25	0.0261**
Group membership	0.86	0.61	1.87	0.0629*
Innovativeness	6.21	4.83	3.31	0.0011***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The t-values measure if there is any statistically significant difference between the characteristics of adopters and non-adopters.

Table 5.3 reveals adopters of all 3 AI technologies [AI with semen from: daughter proven bulls (AIDPB); young bulls (AIYB) and AI with sexed semen (AISS)] are producers with relatively higher educational attainment and are more innovative compared to non-adopters. In addition, adopters of AISS are more likely to be members of producer groups. These findings are consistent with *a priori* expectations given that AISS is a fairly new technology and producer awareness and innovativeness are paramount to early adoption of emerging technologies.

Table 5.3 suggests producers enrolled in the dairy herd improvement program (DHIP) are slightly younger and less experienced but have larger dairy herds as compared to non-adopters. They are also more innovative and on the average interact more with other producers. Adopters of DHIP earn a greater percentage of their income from dairy operations (i.e., rely more on dairy farming) and have higher debt-to-asset ratios. This suggests they are more committed to or dependent on dairy farming and therefore more likely to invest heavily in their farms. Non-adopters of DHIP, however, have more experience in dairy farming, which corroborates Grisham's (2007) assertion that older farmers probably keep and learn from their own historical dairy records and therefore do not consider the benefits of DHIP membership to equal or exceed associated participation fees.

Adopters of personal computers (PCs) are more educated and have larger dairy farms. They are also more likely to belong to a producer group, are more innovative and earn a greater percentage of their income off-farm. All the findings on the characteristics of PC adopters are as expected. For example, given the importance of PCs for the farm's daily record-keeping activities, farms with larger herds are expected to embrace it more since paper recordkeeping gets more cumbersome as the dairy herd grows in size. Moreover, producers with higher education are those more likely to have knowledge of PC use.

Table 5.3: Characteristics of CM technology adopters

Cost-minimizing technologies	Adopters	Non-adopters	|t-value|	Prob>t
AI with semen from daughter proven bulls				
Age group	5.12	5.74	2.14	0.0335**
Debt-to-asset ratio	28.08	12.66	2.56	0.0116**
Experience	23.52	35.11	3.45	0.0007***
Future extension	0.51	0.21	2.27	0.0244**
Innovativeness	5.21	2.30	9.66	0.0001***
Post-sec. Education	0.54	0.25	2.49	0.0134**
AI with semen from young bulls				
Experience	23.45	31.53	2.24	0.0322**
Innovativeness	5.25	3.03	8.43	0.0001***
Off-farm income	8.88	2.46	2.85	0.0062***
Post-sec. Education	0.54	0.37	1.73	0.0851*
AI with sexed semen				
Group membership	0.69	0.57	1.77	0.0784*
Innovativeness	5.88	4.21	9.26	0.0001***
Post-sec. Education	0.61	0.44	2.55	0.0116**
Dairy herd improvement program				
Age group	5.11	5.60	1.88	0.0610*
Debt-to-asset ratio	28.07	16.36	2.86	0.0070***
Dairy income	86.62	76.39	2.38	0.0185**
Dairy herd size	87.10	62.96	2.99	0.0040***
Experience	23.77	30.56	1.83	0.0774*
Future extension	0.52	0.25	2.21	0.0281**
Innovativeness	5.26	2.52	8.58	0.0001***
Quota	75.55	43.23	3.14	0.0029***
Social interaction	3.71	2.70	1.80	0.0770*
Personal computer for farm business				
Dairy income	84.09	89.29	1.83	0.0706*
Dairy herd size	91.16	65.10	2.94	0.0039***
Group membership	0.72	0.34	5.28	0.0001***
Innovativeness	5.32	3.79	6.88	0.0001***
Off-farm income	9.31	3.78	2.79	0.0060***
Post-sec. Education	0.61	0.25	4.73	0.0001***
Quota	78.53	50.40	2.89	0.0045***

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

The t-value measures if there is a statistically significant difference between adopters' and non-adopters' characteristics.

In conclusion, the mean comparison tests used in characterizing adopters of both PE and CM technologies mostly generated results that conform to *a priori* expectations. For example, a capital-intensive technology like TMR is expected to increase adopters' debt-to-asset ratios and also to be suitable only to producers that are running medium- to large-scale operations. In addition, having a family member available to succeed upon a farmer's retirement encourages adoption of such technologies, as the results depict. The importance of producers' innovativeness, higher education, social interactions and membership in groups to technology adoption was well highlighted for both PE and CM technologies in the results. Unfortunately, results on 'average annual milk yield' and 'percent feed cost' variables, which were expected to support the categorization of the technologies into PE and CM, are not significant in almost all the technologies under study. Although GENO adopters spend a significantly lower percentage of their total production costs on feed, this finding underscores the possible CM benefits of GENO rather than its PE benefits. Results on average milk yields for RMS adopters contradict the supposed PE benefits of the technology but, as explained before, this is not a reliable result given the overall low adoption level (6.83% of 205 producers) of RMS in the sample.

5.2 Determinants of adoption of PE and CM dairy technologies

Objective 2 of this thesis is to identify the key variables that affect technology adoption and to estimate their effects. I achieve this by modeling producers' adoption decision with a binary logit model. Since the parameter estimates from a logit model are not intuitive, I interpret the results of the models in terms of odds ratios (ORs).

To enable comparison, I present results for 2 sets of models (Table 5.4 and Table 5.5) fitted using imputed (model 1) and non-imputed (model 2) data sets. Although not true for all variables, in general, variables with more missing observations have higher differences between the ORs of model 1 and 2. For example, the 'succession' variable has 22.34% missing observations (see Appendix A) and the difference between its odd ratio for model 1 and 2 is approximately 10.14. On the other hand, the innovativeness variable has 1.54% missing observations and the difference between its odds ratio for the two models is 0.47. This reflects the somewhat inflating effect of missing observations on estimates of the ORs. In other words, OR estimates are similar for both models except when the particular regressor has high percent of missing observations. Thus, the discussions below are mainly based on results from model 1.

A noticeable outcome from all the logit models is the strong influence of farmers' innovativeness (measured by the total number of technologies in current use on the farm) on the odds of adopting a given dairy technology. According to the results, the odds of current adopters of a given technology adopting other technologies are 2 to 6 times higher compared with current non-adopters. This implies success in previous adoption decisions encourages the adoption of other innovations (similar to the finding in Figure 4.3). Also, this finding possibly suggests the existence of complementarities among the dairy technologies being studied, and that producers may in reality adopt them in groups. The odds ratios for RMS (AIDPB) adoption may be erroneous due to its extremely low (high) overall adoption levels.

The estimates in Table 5.4 on TMR adoption suggest the odds of adopting TMR for a producer with a successor are about 2.5 times more than the odds for a producer with no successor. Farmers with high debt-to-asset ratios are also more likely to be TMR adopters since the results suggest a one percentage point increase in this ratio increases the likelihood of TMR adoption by 3.8%. These findings are both consistent with those in Table 5.2 given the capital-intensive aspect of the technology. Adopters of TMR accumulate more debt and might take a longer period of time to recover their investment costs. Having a family successor therefore could allow a long enough time horizon to realize the full benefits of their investments (Grisham 2007).

Model 1 results suggest that an additional year of experience in dairy farming increases the likelihood of adopting TMR by 16.7%. The size of this effect increases at a decreasing rate based on the sign and significance of the quadratic term of the variable in the model. Another factor that also positively influences TMR adoption is the size of a producer's dairy herd. My results suggest that for every 10 cows added to the herd, producers become 2.3 times more likely to adopt TMR on their farms. This meets *a priori* expectations and confirms the earlier finding in Table 5.2 that TMR feeding is more practical to implement on farms with large herds. Finally, contrary to *a priori* expectations that post-secondary education facilitates a producer's ability to understand and implement more management-intensive technologies, the results indicate post-secondary education actually decreases the likelihood of TMR adoption by 66.2%.

Regarding the adoption of GENO technologies, the results suggest a producer's odds of adopting GENO increases by 5% for every additional year he plans on staying in dairy farming. GENO technologies essentially improve the desirable characteristics of dairy cows. Thus, it can be argued that a producer who plans on staying longer in dairy farming would want to adopt this technology so as to benefit from them on a long term basis. Also, Table 5.4 shows that the odds of GENO adoption decreases by 2.3% for every percentage point increase in a producer's debt-to-asset ratio. This is an indication that as producers become more and more indebted, they are discouraged from adopting technologies even if they believe it is important to future success in the industry.

Table 5.4 suggests producers are 2.1 times more likely to adopt YGBNS for every 10 cows added to their herd. This supports the hypothesis that YGBNS is more suitable for large farms than small farms. Large dairy farms are more likely to have the ability to support or maintain bulls than small farms do. The results in Table 5.4 also show membership in a producer group causes producers to be 3.5 times more likely to adopt RMS compared with non-members. This emphasizes the importance of learning and awareness among dairy farmers in making adoption decisions. Farmers get the opportunity to share and learn from the experience of their colleagues within producer groups. By doing so, they get to discover the benefits and suitability of the RMS technology to their dairy operations.

From Table 5.5, the results suggest producers who earn relatively more off-farm are about 2% and 4.4% less likely to adopt AISS and DHIP, respectively. These findings suggest producers who do not rely exclusively on their dairy farm earnings are less likely to be interested in adopting cost-minimizing technologies like AISS and DHIP. Off-farm earnings are also important in explaining the odds of PC technology adoption. A percentage increase in the proportion of income earned off-farm positively influences the odds of PC technology adoption by 2.3%. Other important determinants of PC technology adoption include having post-secondary education (increases the odds of PC adoption by 314%) and membership in a producer group/organization (increases the odds of PC adoption by 402%). Lastly, the results suggest that for every additional 10 cows, producers are 2.4 times more likely to adopt PC technology. All these findings are consistent with *a priori* expectations as discussed in section 2.2.

Table 5.4: Determinants of adoption of PE technologies – odds ratios

	Total mixed rations		Genotyping		Young genomic bulls in natural service		Robotic milking systems	
Variables	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Succession	2.532*	12.67**	1.532	1.536	0.302**	0.0407***	2.309	4.227
	(1.255)	(13.98)	(0.909)	(1.452)	(0.152)	(0.0437)	(2.773)	(7.172)
Post-sec. Education	0.338**	1.265	2.298	13.08**	0.287**	0.153	0.604	0.712
	(0.167)	(1.075)	(1.237)	(16.92)	(0.157)	(0.179)	(0.384)	(0.517)
Experience	1.167**	1.091	0.978	1.071	1.008	0.906	1.076	0.984
	(0.0805)	(0.103)	(0.0775)	(0.154)	(0.0603)	(0.0657)	(0.156)	(0.108)
Experience squared	0.997**	0.998	1.001	1.000	1.001	1.002**	0.998	0.998
	(0.00125)	(0.00169)	(0.00132)	(0.00243)	(0.000832)	(0.00105)	(0.00231)	(0.00206)
Innovativeness	3.396***	3.866***	5.089***	10.40***	1.495	1.439	2.085*	1.677
	(0.795)	(1.484)	(1.433)	(7.062)	(0.400)	(0.591)	(0.914)	(1.126)
Horizon	0.988	0.909**	1.050*	1.078	1.025	1.070**	0.956	0.864**
	(0.0291)	(0.0417)	(0.0310)	(0.0676)	(0.0223)	(0.0308)	(0.0447)	(0.0580)
Off-farm income	1.003	1.019	0.994	0.981	1.019	1.018	1.019	1.035***
	(0.0105)	(0.0166)	(0.0113)	(0.0142)	(0.0119)	(0.0115)	(0.0126)	(0.0125)
Log of herd size	2.291*	11.40***	0.606	0.280	2.125*	6.937	1.248	2.110
	(1.102)	(9.064)	(0.345)	(0.439)	(0.918)	(8.305)	(0.875)	(2.243)
Debt-to-asset ratio	1.038***	1.063**	0.977**	0.967*	0.996	0.980	1.004	1.034
	(0.0147)	(0.0263)	(0.0109)	(0.0183)	(0.0121)	(0.0147)	(0.0187)	(0.0235)
Group membership	1.464	1.409	2.086	1.517	1.572	9.235**	3.133*	5.817**
	(0.682)	(1.217)	(1.366)	(1.812)	(1.104)	(9.859)	(1.934)	(4.417)
Percent feed cost	5.376	8.109	0.130	0.0141*	1.319	0.540	0.270	0.127
	(8.053)	(17.77)	(0.224)	(0.0324)	(2.067)	(1.113)	(0.903)	(0.496)
Constant	2.06e-05***	1.45e-08***	0.000116***	2.65e-06**	0.000379***	7.86e-06***	0.000226**	0.000481
	(4.88e-05)	(6.80e-08)	(0.000312)	(1.47e-05)	(0.000745)	(3.55e-05)	(0.000894)	(0.00302)

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
n = 205 for Model (1) and 106 for Model (2)
Model (1) = results from data with multiple-imputations
Model (2) = results from data without any imputations for missing observations

Table 5.5: Determinants of adoption of CM technologies – odds ratios

	AI with daughter proven bulls		AI with young bulls		AI with sexed semen		Dairy herd improvement program		Personal Computer	
Variables	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Succession	0.318	0	3.449*	5.240	0.864	0.516	0.357	0.247	0.496	0.638
	(0.489)	(0)	(2.448)	(6.013)	(0.362)	(0.390)	(0.354)	(0.365)	(0.266)	(0.480)
Post-sec. Education	1.979	0	0.480	1.365	1.347	0.811	0.966	0.311	3.142***	1.332
	(3.666)	(0)	(0.330)	(1.552)	(0.510)	(0.525)	(0.936)	(0.719)	(1.396)	(0.850)
Experience	0.886**	0.228	0.946	1.051	1.002	1.026	1.100	1.017	0.937	0.864*
	(0.0519)	(0)	(0.0656)	(0.121)	(0.0437)	(0.0660)	(0.112)	(0.176)	(0.0557)	(0.0752)
Experience squared	1.001	0.993	1.000	0.998	1.001	1.001	0.999	1.000	1.001*	1.002**
	(0.000820)	(0)	(0.000847)	(0.00176)	(0.000657)	(0.000894)	(0.00116)	(0.00182)	(0.000740)	(0.000935)
Innovativeness	18.16***	2.598e+65	5.458***	3.995***	4.360***	7.637***	6.024***	9.184***	1.953***	2.235***
	(20.06)	(0)	(1.665)	(1.292)	(1.308)	(5.245)	(2.736)	(7.297)	(0.362)	(0.626)
Horizon	0.966	1.529	0.964	0.954	1.024	1.047	1.068	1.053	0.973	0.980
	(0.0293)	(0)	(0.0333)	(0.0420)	(0.0215)	(0.0322)	(0.0594)	(0.0712)	(0.0335)	(0.0484)
Off-farm income	0.956**	0.191	1.041**	1.016	0.981**	0.977*	0.956*	0.976	1.023**	1.040**
	(0.0201)	(0)	(0.0193)	(0.0284)	(0.00927)	(0.0119)	(0.0221)	(0.0516)	(0.0115)	(0.0200)
Log of herd size	0.248	0	0.553	0.242	0.634	0.560	0.903	0.990	2.387*	1.647
	(0.272)	(0)	(0.259)	(0.236)	(0.219)	(0.400)	(0.420)	(1.070)	(1.107)	(0.987)
Debt-to-asset ratio	1.026	1.550	0.972*	0.990	0.998	1.000	1.007	0.967	1.002	0.989
	(0.0505)	(0)	(0.0145)	(0.0177)	(0.00955)	(0.0138)	(0.0214)	(0.0441)	(0.0120)	(0.0196)
Group membership	0.00333***	0	0.291*	0.180	0.593	0.563	0.268	0.328	4.021***	4.108**
	(0.00685)	(0)	(0.198)	(0.245)	(0.251)	(0.385)	(0.276)	(0.661)	(1.757)	(2.669)
Percent feed cost	10.34	1.85e+93	0.688	0.671	13.77**	408.3**	0.413	0.0181	0.0523*	0.00922***
	(33.02)	(0)	(1.293)	(1.221)	(16.62)	(1,086)	(0.704)	(0.0481)	(0.0827)	(0.0159)
Constant	84.40	3.697e+132	1.298	23.21	0.000839***	2.44e-05***	0.00700*	0.0364	0.00776**	0.243
	(373.8)	(0)	(2.574)	(86.21)	(0.00152)	(8.95e-05)	(0.0185)	(0.0938)	(0.0182)	(0.764)

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
n = 205 for Model (1) and 106 for Model (2)
Model (1) = results from data with multiple-imputations
Model (2) = results from data without any imputations for missing observations

5.3 Impact of PE technologies on cow productivity and dairy farm performance

The following subsections use results from the propensity score matching (PSM) and endogenous switching regression (ESR) models to assess the impact of PE technology adoption on cow productivity and dairy farm performance. All the PSM models were tested to ensure they met the balancing condition for PSM implementation. I applied 2000 bootstrap replications to calculate the standard errors. The same model specification as used in the logit adoption models were used for the PSM models, the results of which are discussed below. Also, the ESR models were tested using the likelihood ratio (LR) test for joint independence of the 3 equations as suggested by Lokshin and Sajaia (2004) and Di Falco et al. (2011) to ensure that adoption is endogenous.

5.3.1 Impact of PE technologies on cow productivity

Among the 4 PE technologies under investigation, 2 demonstrated significant positive impacts on cow productivity. First was the adoption of DNA genotyping (GENO). Using the kernel and stratification matching methods, the PSM technique suggests the adoption of GENO significantly improves cow productivity (i.e., average annual milk yield) between 65.5 and 67.4 hectolitres of milk per cow per year (see Table 5.6) after controlling for all observable farmer and farm characteristics. Secondly, PSM with the stratification matching algorithm suggests the adoption of TMR improves cow productivity by about 38.65 hectolitres per year. These findings confirm *a priori* expectations given the known benefits of GENO and TMR adoption under suitable conditions (see section 2.2.1 and 2.2.2 respectively). The other finding is the impact of RMS adoption on cow productivity. The PSM models reveal average annual milk yield of RMS adopters is about

37.52 hectolitres lower compared with non-adopters. This is inconsistent with my *a priori* expectation but, as explained earlier, it is possibly due to the low overall adoption level of RMS. Table 5.6 suggests only 14 treated observations were used in matching to numerous control observations. Hence, there is a high likelihood of mismatching and bad matches and these could result in the negative significant results being reported under the kernel and radius matching for RMS adoption.

Table 5.6: Adoption impact on cow productivity – PSM model

	Treated obs.	Control obs.	ATT	Std. Error
Nearest neighbour matching				
Total mixed rations	151	22	11.10	28.71
Genotyping	42	22	43.96	38.27
Young genomic bulls in natural service	23	17	42.36	47.57
Robotic milking systems	14	11	-95.60	74.86
Kernel matching				
Total mixed rations	151	34	33.83	22.21
Genotyping	42	109	65.47**	31.47
Young genomic bulls in natural service	23	149	39.30	42.4
Robotic milking systems	14	172	-37.52**	17.82
Stratification Matching				
Total mixed rations	151	34	38.65*	21.01
Genotyping	42	109	67.40*	32.72
Young genomic bulls in natural service	21	151	47.80	45.55
Robotic milking systems	14	172	-51.53	35.54
Radius matching (r = 0.1)				
Total mixed rations	151	42	32.74	21.64
Genotyping	40	163	51.33	32.95
Young genomic bulls in natural service	22	182	42.88	40.69
Robotic milking systems	14	190	-38.47**	15.61

*** p<0.01, ** p<0.05, * p<0.1
Outcome variable = average annual milk yield
ATT measures the average effect of adoption on adopters' average annual milk yield

Results from the ESR models (see Table 5.7) convey a different message regarding the impact of PE technologies on cow productivity. An LR test of independence of the 3 equations confirmed that adoption of TMR is endogenous (Di Falco et al. 2011; Asfaw et al. 2012). The same test for GENO and YGBNS, contrary to expectations, rejects the null hypothesis that adoption of these technologies is endogenous. This suggests endogeneity is not an issue in those models and hence, needs not to be accounted for.

Table 5.7: Adoption impact on cow productivity – ESR model

Technology	Decision stage: To adopt	Decision stage: Not to adopt	Treatment effects		Std. Err	LR test of independence of outcome equations: Chi-sq	LR test of independence of outcome equations: p-value
Total mixed rations							
Adopters	4.41[a]	4.85[c]	TT =	- 0.43***	0.0709	9.62***	0.0019
Non-adopters	4.16[d]	4.35[b]	TU =	- 0.19**	0.0830		
Genotyping							
Adopters	4.48[a]	4.01[c]	TT =	0.47***	0.1081	1.18	0.2772
Non-adopters	4.44[d]	4.39[b]	TU =	0.05	0.0559		
Young genomic bulls in natural service							
Adopters	4.48[a]	4.04[c]	TT =	0.44***	0.1351	2.52	0.1126
Non-adopters	4.62[d]	4.40[b]	TU =	0.22***	0.0431		

*** p<0.01, ** p<0.05, * p<0.1
a and b = average actual yield outcome for adopters and non-adopters respectively
c and d = average counterfactual yield outcome for adopters and non-adopters respectively
Outcome variable = log of average annual milk yield
TT = impact of adoption on the adopters' average annual milk yield
TU = expected impact of adoption on non-adopters' average annual milk yield if they had adopted the technology (counterfactual)

The results suggest TMR adoption has a significantly negative impact (i.e., 19% to 43% (average of 31%) worse relative to non-adopters) on dairy cow productivity. Although the LR test rejects the null hypothesis of endogeneity in the decision to adopt GENO and YGBNS, the ESR models for these dairy technologies suggest adoption of the technologies positively impacts dairy cow productivity. Average annual milk yields for GENO adopters are about 47% higher while that for YGBNS adopters are on the average 33% higher compared with non-adopters. The ESR model for the impact of RMS adoption failed probably due to the extremely low overall adoption level and is therefore not included in Table 5.7.

5.3.2 Impact of technology use on dairy farm performance

The second part of objective 3 is to examine the effect of PE technology adoption on dairy farm performance. A dairy farm's expenses on feed are a significant proportion of production costs (Richards 1999) and thus, given the data, feed costs as a percentage of total production costs (i.e., percent feed cost) is a good proxy for farm performance. This implies, all things being equal, percent feed cost for a dairy farm, and farm performance are inversely related. Lang (2013) found average percent feed cost for the Ontario industry to be approximately 44.08% and Richards (1999) suggest that extreme percentages are unlikely. This assertion holds for my data since average percent feed cost is 32.32%, somewhat comparable to the provincial average (44.08%). Table 5.8 and Table 5.9 present results of the impacts of PE technology adoption on dairy farm performance from the PSM and ESR models respectively. The ESR model failed for YGBNS and RMS so Table 5.9 only has results on TMR and GENO adoption.

Results from the PSM models (Table 5.8) suggest that among the 4 PE technologies, only the adoption of GENO has statistically significant impact on dairy farm performance. Adoption of GENO also shows to reduce percent feed cost of dairy farms by about 5% to 10.9% (averages at about 8.1% considering the statistically significant estimates from all 4 matching methods). Although some of the other PE technologies show to improve farm performance, the estimates are not statistically significant and also are inconsistent across the different matching methods.

Table 5.8: Adoption impact on dairy farm performance – PSM model

	Treated obs.	Control obs.	ATT	Std. Error
Nearest neighbour matching				
Total mixed rations	151	22	-0.006	0.031
Genotyping	42	20	-0.109**	0.047
Young genomic bulls in natural service	23	20	-0.009	0.056
Robotic milking systems	14	13	0.002	0.057
Kernel matching				
Total mixed rations	151	32	0.026	0.033
Genotyping	42	113	-0.076**	0.037
Young genomic bulls in natural service	23	149	0.021	0.035
Robotic milking systems	14	153	-0.020	0.037
Stratification Matching				
Total mixed rations	151	32	0.030	0.032
Genotyping	42	113	-0.089***	0.033
Young genomic bulls in natural service	20	152	-0.014	0.031
Robotic milking systems	14	153	-0.016	0.041
Radius matching (r = 0.1)				
Total mixed rations	151	38	0.029	0.030
Genotyping	38	163	-0.050**	0.025
Young genomic bulls in natural service	22	182	0.001	0.028
Robotic milking systems	14	191	-0.045	0.040

*** p<0.01, ** p<0.05, * p<0.1
Outcome variable = percent feed cost
ATT = average impact of adoption on the adopters' percent feed cost

Results from the ESR models (Table 5.9) show that TMR adoption significantly improves dairy farm performance by 2% to 20% (average is 11%). Given that the PSM model did not find any significant impact of TMR adoption, this finding from the ESR model for TMR adoption suggest endogeneity is an issue. The LR test for TMR adoption consequently confirmed endogeneity at the 10% significance level. Although not statistically significant, GENO adoption improves farms' percent feed cost by about 2% according to the ESR model (Table 5.9).

Table 5.9: Adoption impact on dairy farm performance – ESR model

Technology	Decision stage: To adopt	Decision stage: Not to adopt	Treatment effects		Std. Err	LR test of independence of outcome equations: Chi-sq	LR test of independence of outcome equations: p-value
Total mixed rations							
Adopters	0.32[a]	0.31[c]	TT =	- 0.20***	0.0069	3.40*	0.0654
Non-adopters	0.52[d]	0.33[b]	TU =	- 0.02**	0.0091		
Genotyping							
Adopters	0.30[a]	0.33[c]	TT =	- 0.02	0.0085	0.17	0.6817
Non-adopters	0.32[d]	0.33[b]	TU =	0.00	0.0036		

*** p<0.01, ** p<0.05, * p<0.1
a and b = average actual yield outcome for adopters and non-adopters respectively
c and d = average counterfactual yield outcome for adopters and non-adopters respectively
Outcome variable = percent feed cost
TT = impact of adoption on the adopters' percent feed cost
TU = expected impact of adoption on non-adopters' percent feed cost if they had adopted the technology (counterfactual)

CHAPTER 6: SUMMARY AND CONCLUSIONS

6.1 Introduction

The primary goal of this study was to characterize technology use on Ontario dairy farms and empirically estimate the effect of certain dairy technologies on cow productivity and farm performance. I was particularly interested in identifying which type of technology (productivity-enhancing (PE) or cost-minimizing (CM)) is more commonly used. This is of interest because the current policy regime, among other things, hinders Canada from negotiating international trade agreements. Given Canada's current interest in liberalizing international trade, supply management is likely to be affected in ways that will introduce foreign competition. Therefore, it is important for Canadian producers to be prepared, in terms of technology use, in order to be competitive on the international platform. Moreover, adoption of the appropriate technologies in the dairy industry could benefit both the environment and the Canadian public in terms of low greenhouse gas emissions and lower retail prices.

Working with the knowledge that supply management negatively influences productivity of the Canadian dairy industry (Jeffrey 1992; Richards 1996) and also the theory that under supply management, producers minimize costs subject to output constraints (Doyon 2011), I tested the hypothesis that Canadian producers adopt more CM than PE technologies. Subsequently, I investigated the characteristics of adopters of the various technologies and the determinants of adoption for each of the dairy technologies studied. To empirically determine how important it will be for Canadian dairy producers to adopt more PE technologies, I assessed the impact of PE technology adoption on cow productivity and dairy farm performance. The specific objectives for this thesis, therefore, were to:

1) calculate adoption levels and characterize farms adopting dairy technologies;
2) find the determinants of adoption of PE and CM dairy technologies; and
3) assess the impact of PE technology adoption on cow productivity and the performance of dairy farms in Ontario.

6.2 Summary of results

In order to investigate Ontario dairy producers' technology adoption behaviour under supply management, I grouped 9 dairy technologies into PE and CM categories. Results from a one-tailed mean comparison test validated the hypothesis that Canadian dairy producers are more inclined toward the adoption of CM than PE technologies. PE technologies had statistically significant lower (at the 1% level) adoption levels across all 3 farm-size groups [i.e., small (≤50 cows), medium (51-100 cows) and large scale (>100 cows) operations] when compared with corresponding CM categories. This observation emphasizes how policy has shaped technology use in the Canadian dairy industry (Jeffrey 1992; Richards 1996; Rodenburg 2012).

An attempt to characterize adopters (or adopting farms) based on their observed characteristics showed that in general, these characteristics and those of the technology in question are important in determining the kind of technologies producers (or farms) adopt. For example, adopters of capital-intensive technologies like Total Mixed Rations (TMR) as expected, operate larger herds, have higher debt-to-asset ratios, and were more likely to have a successor. Also, characteristics such as producers' innovativeness, education, and group membership were shown to be important and common among adopters of both PE and CM technologies. Unexpectedly, however, differences that were expected between adopters and non-adopters regarding their farms' 'average annual milk yield' and 'percent feed cost' variables were mostly insignificant and thus, could not be used to support how I categorized the technologies. In general, the suitability of a technology to producers' scale/size of operations seem very important to producers when making adoption decisions.

Regarding the determinants of adoption of PE and CM technologies, results from the binary logit models highlighted the importance of producers' innovativeness on their odds of adopting any given dairy technology. This suggests the existence of possible complementarities among most of the dairy technologies and it is possible that producers might actually be adopting technologies in groups. Further empirical evidence to support the existence of complementarities is shown in Appendix B.

In assessing the impact of technology adoption on cow productivity, two different econometric models were used. These are: 1) propensity score matching (PSM); and 2) endogenous switching regression (ESR) models. Although both the PSM and ESR are econometrically appropriate to handle the potential self-selection associated with producer adoption decisions, the PSM method only controls for observable characteristics while the ESR controls for both observable and unobservable characteristics of the producer and the dairy farm. Results from the PSM models show that adoption of DNA genotyping (GENO) and TMR positively impact cow productivity. GENO adoption increased farms' average annual milk yield by about 65.5 to 67.4 hectolitres, whereas TMR adoption increases cow productivity by about 38.65 hectolitres per cow per year. According to the ESR model, however, adopting TMR decreases cow productivity by about 19% to 43%. Although a likelihood ratio test for the endogeneity of the adoption decision failed for GENO and

YGBNS, estimates of their impact on cow productivity were positive and ranged from 5% to 47% and 22% to 44%, respectively.

The last objective was to assess the impact of PE technology adoption on dairy farm performance. PSM and ESR models were used and the PSM model results showed that the adoption of GENO improves farm performance by 8.1% on average. Using the ESR model, I observed TMR adoption, (which did not show any significant impact on farm performance in the PSM model) significantly improves performance by about 11% on the average. This indicated endogeneity as an issue in the adoption of TMR and a likelihood ratio test confirmed endogeneity at the 10% significance level. Although not significant, GENO adoption also showed to improve performance by about 2%.

6.3 Conclusions

This study found that Ontario dairy producers' technology adoption behaviour is likely influenced by supply management. The output constraint imposed by supply management has caused producers to be more inclined toward the adoption of CM than PE technologies. Another reason for the observed trend in the adoption of dairy technologies could be that the nature[10] of the cost-of-production pricing formula used by the CDC rewards the adoption of CM technologies over PE technologies. Finally, the adoption of some PE technologies (e.g., GENO and TMR) showed good potential to improve cow productivity. The adoption of GENO and TMR are also important in improving dairy farm performance, and should thus be encouraged through group-focused producer education.

---

[10] The cost-of-production pricing formula assigns 40% weighting to production costs, and 30% each to consumers personal disposable income and consumer price index (Canadian Dairy Commission 2008; Goldfarb 2009).

This is because the results show producer interactions with other producers encourages adoption of appropriate technologies.

In sum, technologies are important in improving both the productivity and performance of the Canadian dairy industry. Canadian producers will therefore need to not only consolidate and expand their dairy operations (Jeffrey 1992), but will also need to adopt more PE technologies in order to be internationally competitive as well as bring gains to the environment (i.e., low greenhouse gas emissions) and the Canadian society (i.e., lower retail prices).

6.4 Limitations and suggestion for future research

The major limitations of this study were the scope, unavailability of specific data such as farm profits – as an additional measure of farm performance, and the cross-sectional nature of the available data. If panel data were available, it would have helped capture some dynamics that could not be revealed by cross-sectional data. Producers were sampled only from Ontario and aside from the low response rate, data from other provinces would have helped reveal any regional differences that might exist in adoption patterns. A larger sample size would also improve the results with more degrees of freedom. Moreover, I believe the 'percent feed cost' variable is an inadequate measure of dairy farm performance. A variable capturing producer's per unit cost of production or farm profits would have been preferred if available. Although Lang (2013) established the average percent feed cost for the Ontario industry at approximately 44.08%, it is still less than half of the total variable costs of production. Thus, the remaining variable cost components could possibly alter farms' performance measures and present a different picture. Further research is therefore necessary and must address the above limitations, and also consider a wider range of dairy technologies and management practices to obtain a comprehensive picture of how producers' technology adoption behaviour has been influenced by the policy environment in the Canadian dairy industry.

REFERENCES

AAFC. 1995. The Canadian Dairy Sector: Structure, Performance and polices. Retrieved September 15, 2014, from ageconsearch.umn.edu/bitstream/16950/1/ag960011.pdf

AAFC. 2013. *Canada's Dairy Industry at a Glance*. ISSN 1923-6905, AAFC No: 12051E. Retrieved from www.dairyinfo.gc.ca on October 02, 2014

AAFC. 2014. *Statistics of the Canadian Dairy Industry - 2014 Edition*. Ottawa, ON. Retrieved from http://dairyinfo.gc.ca/ on September 05, 2014

Abbassi, A., Bonroy, O., and Gervais, J.-P. 2008. Dairy Trade Liberalization Impacts in Canada. *Canadian Journal of Agricultural Economics*, 56(3), 313–335.

Adesina, A. A., and Zinnah, M. M. 1993. Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone. *Agricultural Economics*, 9(4), 297–311.

Ali, A., and Abdulai, A. 2010. The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of Agricultural Economics*, 61(1), 175–192.

Allison, P. D. 2000. Multiple Imputation for Missing Data A Cautionary Tale. *Sociological Methods & Research*, 28(3), 301–309.

An, H. 2013. The Disadoption of rbST and Its Economic Impact: A Switching Regression Approach. *Applied Economic Perspectives and Policy*, 35(3), 528–549.

Asfaw, S., Kassie, M., Simtowe, F., and Lipper, L. 2012. Poverty Reduction Effects of Agricultural Technology Adoption: A Micro-evidence from Rural Tanzania. *Journal of Development Studies*, 48(9), 1288–1305.

Austin, P. C. 2011. An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate Behavioral Research*, 46(3), 399–424.

Azzam, A. M., Azzam, S. M., Keele, J. W., and Keown, J. F. 1989. The economic value of dairy herd improvement information in a sample of midwestern dairy farms. *Journal of Dairy Science*, 72(5), 1296–1301.

Barber, K. A. 1983. Maximizing the impact of dairy and beef bulls through breeding technology. *Journal of Dairy Science*, 66(12), 2661–2671.

Barham, B. L., Foltz, J. D., Jackson-Smith, D., and Moon, S. 2004. The Dynamics of Agricultural Biotechnology Adoption: Lessons from series rBST Use in Wisconsin, 1994-2001. *American Journal of Agricultural Economics*, 86(1), 61–72.

Barnes, M. A., Pearson, R. E., and Lukes-Wilson, A. J. 1990. Effects of milking frequency and selection for milk yield on productive efficiency of Holstein cows. *Journal of Dairy Science*, 73(6), 1603–1611.

Barrett, C. B., Moser, C. M., McHugh, O. V, and Barison, J. 2004. Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers. *American Journal of Agricultural Economics*, 86(4), 869–888.

Bell, R. 2009. Long-term Strategic Planning of Dairy Businesses. In *Advances in Dairy Technology* (pp. 25 – 39). Western Canadian Dairy Seminar.

Bewley, J. 2013. New Technologies in Precision Dairy Management. In *Advances in Dairy Technology* (Vol. 25, pp. 141 – 159). Western Canadian Dairy Seminar.

Boehlje, M. 1992. Alternative models of structural change in agriculture and related industries. *Agribusiness*, 8(3), 219–231.

Cairns, P., and Hanmore, J. 2013. Ontario Dairy Farm Accounting Project (ODFAP) - Annual Report 2013. Mississauga, Ontario: Dairy Farmers of Ontario. Retrieved from https://www.milk.org/Corporate/pdf/Publications-ODFAPReport.pdf

Caliendo, M., and Kopeinig, S. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1), 31–72.

Cameron, A. C., and Trivedi, K. P. 2005. *Microeconometrics: methods and applications*. Cambridge university press.

Campos, M. S., Wilcox, C. J., Head, H. H., Webb, D. W., and Hayen, J. 1994. Effects on production of milking three times daily on first lactation Holsteins and Jerseys in Florida. *Journal of Dairy Science*, 77(3), 770–773.

Canadian Dairy Commission. **2008**. *P5 Fluid Pricing Formula: Methodology and Indices Used to Calculate Fluid Target Price Increase as of February 1, 2007*. Ottawa, ON.

Canadian Dairy Commission. **2013**. Production. *The Industry*. Retrieved May 11, 2015, from http://www.cdc-ccl.gc.ca/CDC/index-eng.php?id=3801

Capper, J. L., Castañeda-Gutiérrez, E., Cady, R. A., and Bauman, D. E. 2008. The environmental impact of recombinant bovine somatotropin (rbST) use in dairy production. *Proceedings of the National Academy of Sciences*, 105(28), 9668–9673.

Cardona, H. 1999. Analysis of policy alternatives in the implementation of a coastal nonpoint pollution control program for agriculture. *Unpublished Ph. D. Thesis, Dept. of Agricultural Economics and Agribusiness, Louisiana State University*.

Cassell, B. 2001. Using DHI Records to Make Culling Decisions, Lactation Ratings, ERPA's, and Predicted Producing Abilities. Virginia Cooperative Extension. Retrieved April 18, 2015, from http://pubs.ext.vt.edu/404/404-083/404-083.html

Caudill, S. B., and Jackson, J. D. 1989. Measuring marginal effects in limited dependent variable models. *The Statistician*, 38(3), 203–206.

CDIC. **2013a**. Dairy Facts and Figures - The Processing Sector. Retrieved September 10, 2014, from http://dairyinfo.gc.ca

CDIC. **2013b**. Dairy genetic material trade - Overview of Canadian dairy genetics exports. Retrieved September 5, 2014, from http://www.dairyinfo.gc.ca/index_e.php?s1=dff-fcil&s2=imp-exp&s3=gen

CDIC. **2014**. Number of Farms, Dairy Cows and Heifers - Dairy Facts and Figures. Retrieved September 2, 2014, from http://dairyinfo.gc.ca/index_e.php?s1=dff-fcil&s2=farm-ferme&s3=nb

Centre for International Economics. **2009**. Benefits of Trade and Liberalisation. Canberra and Sydney: Prepared for Australia Department of Foreign Affairs and Trade.

Charlebois, S., and Astray, T. 2012. *The Future of the Canadian Dairy Sector: In a Post Supply Management Era*. Policy Series No. 128. Retrieved from http://www.fcpp.org/files/1/PS128_DairyPostEra_MR22F5.pdf

Chen, K., and Meilke, K. 1998. The simple analytics of transferable production quota: Implications for the marginal cost of Ontario milk production. *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, 46(1), 37–52.

Cressie, N. A. C., and Whitford, H. J. 1986. How to Use the Two Sample t-Test. *Biometrical Journal*, 28(2), 131–148.

Curtis, M. D., and Grossniklaus, U. 2007. Plant Genetics and Development. In K. Roberts (Ed.), *Handbook of Plant Science, Vol. 2* (p. 331). John Wiley & Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, England.

David, P. A. 1969. *A Contribution to the Theory of Diffusion*. Research Center in Economic Growth, Stanford University.

Dehejia, R. H., and Wahba, S. 2002. Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, 84(1), 151–161.

DeLaval. **2013**. Automatic milking. Retrieved August 5, 2014, from http://www.delaval.com/en/-/Product-Information1/Milking/Systems/Automatic/

Delgado, C., Narrod, C., and Tiongco, M. 2008. *Determinants and implications of the growing scale of livestock farms in four fast-growing developing countries*. IFPRI Research Report No. 157. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1275538 on March 03, 2015

DFC. **2014**. What is supply management. *Dairy Farmers of Canada*. Retrieved September 5, 2014, from http://www.dairyfarmers.ca/what-we-do/supply-management

DFO. **2014**. *The Ontario Milk Industry*. ON, Canada. Retrieved from www.milk.org on November 19, 2014

Di Falco, S., Veronesi, M., and Yesuf, M. 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829–846.

Doyon, M. 2011. Canada's Dairy Supply Management: Comprehensive Review and Outlook for the Future. *Center for Interuniversity Research and Analysis on Organizations. Pour Discussion. 2011DT-01. Montreal. October*.

Edwards, G. 2003. The story of deregulation in the dairy industry. *Australian Journal of Agricultural and Resource Economics*, 47(1), 75–98.

El-Osta, H. S., and Johnson, J. 1998. *Determinants of financial performance of commercial dairy farms*. US Department of Agriculture, Economic Research Service. Retrieved from http://www.ers.usda.gov/media/929960/tb1859a.pdf on January 07, 2015

El-Osta, H. S., and Morehart, M. J. 2000. Technology adoption and its impact on production performance of dairy operations. *Review of Agricultural Economics*, 22(2), 477–498.

Feder, G., Just, R. E., and Zilberman, D. 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33(2), 255–298.

Feder, G., and Umali, D. L. 1993. The adoption of agricultural innovations: a review. *Technological Forecasting and Social Change*, 43(3), 215–239.

Federated Farmers of New Zealand. **2005**. *Life After Subsidies - The New Zealand Farming Experience - 20 Years Later* -. Wellington. Retrieved from http://www.fedfarm.org.nz/files/2005---Life-after-subsidies---the-NZ-experience.pdf

Fernandez-Cornejo, J., Daberkow, S., and McBride, W. D. 2001. Decomposing the size effect on the adoption of innovations: Agrobiotechnology and precision agriculture. *AgBioForum*, 4(2), 124–136.

Foltz, J. D., and Chang, H.-H. 2002. The adoption and profitability of rbST on Connecticut dairy farms. *American Journal of Agricultural Economics*, 84(4), 1021–1032.

Foote, R. H. 1996. Review: Dairy cattle reproductive physiology research and management—Past progress and future prospects. *Journal of Dairy Science*, 79(6), 980–990.

Gabre-Madhin, E., Barrett, C., and Dorosh, P. 2002. *Technological change and price effects in agriculture: Conceptual and comparative perspectives* (No. 62). *Ethiopian Development Research Institute International Food Policy Research Institute*. Washington, D.C. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=601277 on February 06, 2015

Gillespie, J. M., Davis, C. G., and Rahelizatovo, N. C. 2004. Factors influencing the adoption of breeding technologies in US hog production. *Journal of Agricultural and Applied Economics*, 36(1), 35–48.

Goldfarb, D. 2009. *Making Milk: The Practices, Players, and Pressures Behind Dairy Supply Management*. Ottawa, ON: Conference Board of Canada. Retrieved from http://www.conferenceboard.ca/e-library/abstract.aspx?did=3294

González, V., Ibarrarán, P., Maffioli, A., and Rozo, S. 2009. *The Impact of Technology Adoption on Agricultural Productivity: The Case of the Dominican Republic*. Inter-American Development Bank, Office of Evaluation and Oversight (OVE). Retrieved from http://services.iadb.org/wmsfiles/products/Publications/2191162.pdf on March 11, 2014

Goverment of Canada. **2014**. Technical Summary of the Final Negotiated Outcomes (October 2013). Retrieved June 17, 2014, from http://international.gc.ca/trade-agreements-accords-commerciaux/agr-acc/ceta-aecg/understanding-comprendre/technical-technique.aspx?lang=eng#p2

Government of Australia. **2008**. Advancing agriculture reform in the EU and Australia. Retrieved April 8, 2015, from http://catalogue.nla.gov.au/Record/4503031

Greene, W. H. 2003. *Econometric Analysis* (5th ed.). India: Pearson Education Inc.

Griliches, Z. 1957. Hybrid corn: An exploration in the economics of technological change. *Econometrica*, 25(4), 501–522.

Grisham, E. 2007. Record-keeping systems adoption by Louisiana dairy farmers. Louisiana State University and Agricultural and Mechanical College. (MSc. Thesis).

Grisham, E., and Gillespie, J. 2007. Record-keeping technology adoption in the Louisiana dairy industry. In *Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meetings* (pp. 3–7). Mobile, Alabama.

Hansen, L. 2013. The Welfare Effects due to Canadian Dairy Supply Management. Acadia University. Retrieved from http://economics.acadiau.ca/tl_files/sites/economics/resources/Theses/Luke Hansen - The_welfare_effects_due_to_Canadian_dairy_supply_management.pdf

Heckman, J. J., Ichimura, H., and Todd, P. E. 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64(4), 605–654.

Heckman, J., Tobias, J. L., and Vytlacil, E. 2001. Four parameters of interest in the evaluation of social programs. *Southern Economic Journal*, 68(2), 211–223.

Heikkilä, A., Vanninen, L., and Manninen, E. 2010. Economics of Small-Scale Dairy Farms Having Robotic Milking. In *Progressive Dairy Operators*. Toronto, ON. Canada. Retrieved from http://register.precisiondairy2010.com/proceedings/s3heikkila.pdf

Hennessy, T., and Heanue, K. 2012. Quantifying the Effect of Discussion Group Membership on Technology Adoption and Farm Profit on Dairy Farms. *The Journal of Agricultural Education and Extension*, 18(1), 41–54.

Hill, R. C., Griffiths, W. E., and Judge, G. G. 2001. *Undergraduate Econometrics* (2nd ed.). John Wiley & Sons Inc.

Hillers, J. K., Thonney, S. C., and Gaskins, C. T. 1982. Economic comparison of breeding dairy cows artificially versus naturally. *Journal of Dairy Science*, 65(5), 861–865.

Hoag, D. L., Ascough, J. C., and Frasier, W. M. 1999. Farm computer adoption in the Great Plains. *Journal of Agricultural and Applied Economics*, 31(1), 57–68.

Holstein Canada. **2014**. The Canadian dairy industry. Retrieved October 18, 2014, from http://www.holstein.ca/Public/en/About_Us/The_Canadian_Dairy_Industry#

Illumina. **2014**. BovineSNP50 v2 DNA Analysis BeadChip. Retrieved December 16, 2014, from http://products.illumina.com/products/bovine_snp50_whole-genome_genotyping_kits.html

Jeffrey, S. R. 1992. Efficiency in Milk Production: A Canada-U.S. Comparison. *Canadian Journal of Agricultural Economics*, 40(4), 653–662.

Kaaya, H., Bashaasha, B., and Mutetikka, D. 2005. Determinants of utilisation of artificial insemination (AI) services among Ugandan dairy farmers. In *African crop science conference proceedings* (Vol. 7, pp. 561–567).

Kapa Biosystems. **2014**. Genotyping. Retrieved December 15, 2014, from http://www.kapabiosystems.com/product-applications/applications/qpcr/genotyping/

Kassie, M., Shiferaw, B., and Muricho, G. 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development*, 39(10), 1784–1795.

Katchova, A. 2013. Propensity Score Matching. Retrieved December 15, 2014, from https://sites.google.com/site/econometricsacademy/econometrics-models/propensity-score-matching

Khanal, A. R., and Gillespie, J. 2013. Adoption and productivity of breeding technologies: evidence from US dairy farms. *AgBioForum*, 16(1), 53–65.

Khanal, A. R., and Gillespie, J. M. 2011. Adoption and Profitability of Breeding Technologies on United States Dairy Farms. In *2011 Annual Meeting, February 5-8, 2011, Corpus Christi, Texas*. Southern Agricultural Economics Association.

Khanal, A. R., Gillespie, J., and MacDonald, J. 2010. Adoption of technology, management practices, and production systems in US milk production. *Journal of Dairy Science*, 93(12), 6012–6022.

Kijima, Y., Otsuka, K., and Sserunkuuma, D. 2008. Assessing the impact of NERICA on income and poverty in central and western Uganda. *Agricultural Economics*, 38(3), 327–337.

Kilpatrick, S. 1996. *Change, Training and Farm Profitability. A National Farmers Federation Discussion Paper. National Focus* (Vol. 10). Kingston, Austrialia: ERIC. Retrieved from http://eric.ed.gov/?id=ED407503 on January 13, 2015

Klotz, C., and Sana, A. 1995. The role of information in technology adoption: The case of rbST in the California dairy industry. *Review of Agricultural Economics*, 17(3), 287–298.

Kruip, T. A. M., Stefanowska, J., and Ouweltjes, W. 2000. Robot milking and effect on reproduction in dairy cows: a preliminary study. *Animal Reproduction Science*, 60(1), 443–447.

Kulasekera, K. 2013. Statistical Summary of Ontario Agriculture. *OMAFRA*. Retrieved February 20, 2015, from http://www.omafra.gov.on.ca/english/stats/agriculture_summary.htm#first

Lammers, B. P., Heinrichs, J., and Ishler, V. A. 2003. Use of total mixed rations (TMR) for dairy cows. DAS 94-25 IVE/E. University Park, PA. Retrieved from http://extension.psu.edu/animals/dairy/nutrition/nutrition-and-feeding/diet-formulation-and-evaluation/use-of-total-mixed-rations-tmr-for-dairy-cows/at_download/file

Lang, B. 2013. Summary of Ontario 2011 Dairy Farm Income and Expenses. *Ontario Ministry of Agriculture, Food and Rural Affairs*. Retrieved April 17, 2015, from http://www.omafra.gov.on.ca/english/livestock/dairy/facts/info_rumnov2012.htm

Linn, J. 2014. Feeding total mixed rations. *Dairy Extension*. Retrieved October 4, 2014, from http://www.extension.umn.edu/agriculture/dairy/feed-and-nutrition/feeding-total-mixed-rations/

Lokshin, M., and Sajaia, Z. 2004. Maximum likelihood estimation of endogenous switching regression models. *Stata Journal*, 4(3), 282–289.

Mansfield, E. 1963. The speed of response of firms to new techniques. *The Quarterly Journal of Economics*, 77(2), 290–311.

Marra, M. C., Hubbell, B. J., and Carlson, G. A. 2001. Information quality, technology depreciation, and Bt cotton adoption in the Southeastern US. *Journal of Agricultural and Resource Economics*, 26(1), 158–175.

Massey, C., Morriss, S., Alpass, F., and Flett, R. 2004. A framework for building technological learning: Evidence from the New Zealand dairy industry. *Journal of Extension*, 42(3).

Matulich, S. C. 1978. Efficiencies in large-scale dairying: incentives for future structural change. *American Journal of Agricultural Economics*, 60(4), 642–647.

Mayen, C. D., Balagtas, J. V, and Alexander, C. E. 2010. Technology adoption and technical efficiency: organic and conventional dairy farms in the United States. *American Journal of Agricultural Economics*, 92(1), 181–195.

McBride, W. D., Short, S., and El-Osta, H. 2004. The adoption and impact of bovine somatotropin on US dairy farms. *Applied Economic Perspectives and Policy*, 26(4), 472–488.

Mishra, A. K., and Williams, R. P. 2006. Internet access and use by farm households. In *2006 Annual meeting, July 23-26, Long Beach, CA*. American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association).

Murray, B. 2012. Dairy Genomic Selection. ISSN 1198-712X, Agdex#: 410/31, Order #: 12-023: Ontario Ministry of Agriculture, Food and Rural Affairs Factsheet -

Queen's printer for Ontario. Retrieved from http://www.omafra.gov.on.ca/english/livestock/dairy/facts/12-023.htm on March 02, 2015

National Institutes of Health - National Human Genome Research Institute. **2004**. Bovine Genome Assembled - International Effort Makes Data Freely Available to Scientists Worldwide. Retrieved May 14, 2015, from http://www.genome.gov/12512874

Negatu, W., and Parikh, A. 1999. The impact of perception and other factors on the adoption of agricultural technology in the Moret and Jiru Woreda (district) of Ethiopia. *Agricultural Economics*, 21(2), 205–216.

Nowak, P. 1992. Why farmers adopt production technology Overcoming impediments to adoption of crop residue management techniques will be crucial to implementation of conservation compliance plans. *Journal of Soil and Water Conservation*, 47(1), 14–16.

O'brien, R. M. 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity*, 41(5), 673–690.

Olynk, N. J., and Wolf, C. A. 2007. Expected net present value of pure and mixed sexed semen artificial insemination strategies in dairy heifers. *Journal of Dairy Science*, 90(5), 2569–2576.

OMAFRA. **2012**. Robotic Milking of Dairy Cows. *DAIRY*. Retrieved October 1, 2014, from http://www.omafra.gov.on.ca/english/livestock/dairy/robotic/index.html

Painter, M. J. 2007. A comparison of the dairy industries in Canada and New Zealand. *Journal of International Farm Management*, 4(1), 41–60.

Pannell, D. J., Marshall, G. R., Barr, N., Curtis, A., Vanclay, F., and Wilkinson, R. 2006. Understanding and promoting adoption of conservation practices by rural landholders. *Australian Journal of Experimental Agriculture*, 46(11), 1407–1424.

Peng, C.-Y. J., and So, T.-S. H. 2002. Logistic regression analysis and reporting: A primer. *Understanding Statistics: Statistical Issues in Psychology, Education, and the Social Sciences*, 1(1), 31–70.

Petkantchin, V. 2006. How Australia got out of supply management - A lesson for Canada: Milk prices fell from 18% to 29%. *National Post*. Retrieved April 8, 2015, from http://www.iedm.org/fr/2668-how-australia-got-out-of-supply-management-a-lesson-for-canada-milk-prices-fell-from-18-to-29-

Prasada, P., Bredahl, M. E., and Wigle, R. 2010. Market impacts of technological change in Canadian agriculture. *Canadian Journal of Agricultural Economics*, 58(2), 235–247.

Prokopy, L. S., Floress, K., Klotthor-Weinkauf, D., and Baumgart-Getz, A. 2008. Determinants of agricultural best management practice adoption: evidence from the literature. *Journal of Soil and Water Conservation*, 63(5), 300–311.

Putler, D. S., and Zilberman, D. 1988. Computer use in agriculture: evidence from Tulare County, California. *American Journal of Agricultural Economics*, 70(4), 790–802.

Rahelizatovo, N. C., and Gillespie, J. M. 2004. The adoption of best-management practices by Louisiana dairy producers. *Journal of Agricultural and Applied Economics*, 36(1), 229–240.

Rahm, M. R., and Huffman, W. E. 1984. The adoption of reduced tillage: the role of human capital and other variables. *American Journal of Agricultural Economics*, 66(4), 405–413.

Rao, E. J. O., Brümmer, B., and Qaim, M. 2012. Farmer participation in supermarket channels, production technology, and efficiency: The case of vegetables in Kenya. *American Journal of Agricultural Economics*, 94(4), 891–912.

Reeve, I. J., and Black, A. W. 1998. *Improving Farmers' Management Practices: Through Learning and Group Participation: a Report for the Rural Industries Research and Development Corporation*. RIRDC. Retrieved from https://rirdc.infoservices.com.au/items/98-071 on December 15, 2014

Reilly, J. M. 1988. *Cost-reducing and Output-enhancing Technologies*. US Dept. of Agriculture, Economic Research Service.

Richards, T. J. 1996. The effect of supply management on dairy productivity. *The Canadian Journal of Economics*, 29(2), 458–462.

Richards, T. J. 1999. Positioning Your Dairy Farm Business for a Profitable Future - A Western Canadian Perspective. In *Advances in Dairy Technology*. Western Canadian Dairy Seminar. Retrieved from http://www.wcds.ca/proc/1996/wcd96175.htm on Oct. 09, 2014

Rodenburg, J. 2011. Robotic Milking has Big Labour Saving Benefits. *Time for Technology*. Retrieved October 3, 2014, from http://dairylogix.com/14- Robotic Milking has big labour saving benefits.pdf

Rodenburg, J. 2012. Precision Dairy Management and the Future of Dairy Production in Ontario. Ontario Ministry of Agriculture, Food and Rural Affairs Factsheet -

Queen's printer for Ontario. Retrieved from http://www.omafra.gov.on.ca/english/livestock/dairy/facts/07-065.htm on October 16, 2014

Rogers, E. M. 2003. *Diffusion of Innovations* (5th ed.). New York: Free Press.

Rosenbaum, P. R., and Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41–55.

Rotz, C. A., Coiner, C. U., and Soder, K. J. 2003. Automatic milking systems, farm size, and milk production. *Journal of Dairy Science*, 86(12), 4167–77.

Rubin, D. B. 1987. *Multiple Imputation for Nonresponse in Surveys*. *Harvard University*. John Wiley & Sons.

Saha, A., Love, H. A., and Schwart, R. 1994. Adoption of emerging technologies under output uncertainty. *American Journal of Agricultural Economics*, 76(4), 836–846.

Schmitz, A. 1983. Supply Management in Canadian Agriculture: An Assessment of the Economic Effects. *Canadian Journal of Agricultural Economics*, 31(2), 135–152.

Schmitz, A. 2008. Canadian Agricultural Programs and Policy in Transition. *Canadian Journal of Agricultural Economics*, 56(4), 371–391.

Schmitz, A., Furtan, H., and Baylis, K. 2010. *Agricultural Policy, Agribusiness, and Rent-Seeking Behavior*. University of Toronto Press.

Schmitz, A., and Schmitz, T. G. 1994. Supply Management: The Past and Future. *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, 42(2), 125–148.

Schraufnagel, S. 2007. *Technology Systems and Business Performance on Wisconsin Dairy Farms.* University of Wisconsin-River Falls. Retrieved from http://cdp.wisc.edu/pdf/TechSYSTEM&FinPerfOnWI DairyFarms2.pdf on December 2014

Seidel Jr, G. E. 1984. Applications of embryo transfer and related technologies to cattle. *Journal of Dairy Science*, 67(11), 2786–2796.

Slade, P. 2011. The Impact of Government Institutions on Dairy Farm Efficiency: A Comparison of Ontario and New York Dairy Farms. The University of Guelph. Retrieved from https://atrium.lib.uoguelph.ca/xmlui/bitstream/handle/10214/3027/mythesis.pdf?sequence=1 on October 05, 2014

Smith, J. A., and Todd, P. E. 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125(1), 305–353.

Smith, J. W., Ely, L. O., Graves, W. M., and Gilson, W. D. 2002. Effect of milking frequency on DHI performance measures. *Journal of Dairy Science*, 85(12), 3526–3533.

Staciwa, A. 2014. GDP by Manufacturing Industries, Ontario, 2007-2013. *OMAFRA, STATISTICS , Economic Indicators*. Retrieved October 4, 2014, from http://www.omafra.gov.on.ca/english/stats/economy/gdp_manuf.htm

Stefanides, Z., and Tauer, L. W. 1999. The empirical impact of bovine somatotropin on a group of New York dairy farms. *American Journal of Agricultural Economics*, 81(1), 95–102.

Stockdale, C. R. 2006. Influence of milking frequency on the productivity of dairy cows. *Australian Journal of Experimental Agriculture*, 46(7), 965–974.

Studenmund, A. H. 2005. *Using econometrics: A practical guide 5th Edition*. Pearson Addison Wesley; ISBN: 0-321-31649-5.

Sunding, D., and Zilberman, D. 2001. The agricultural innovation process: research and technology adoption in a changing agricultural sector. In *Handbook of agricultural economics* (Vol. 1, pp. 207–261). Elsevier.

Tauer, L. W. 2001. The estimated profit impact of recombinant bovine somatotropin on New York dairy farms for the years 1994 through 1997. *AgBioForum*, 4(2), 115–123.

Tauer, L. W. 2005. The impact of recombinant bovine somatotropin on dairy farm profits: A switching regression analysis. *AgBioForum*, 8(1), 473–478.

Tauer, L. W. 2006. Impact of recombinant bovine somatotropin on dairy farm cost of production: Evidence from multiyear data. *AgBioForum*, 9(2), 79–83.

Tauer, L. W. 2009. Estimation of treatment effects of recombinant bovine somatotropin using matching samples. *Applied Economic Perspectives and Policy*, 31(3), 411–423.

The Conference board of Canada. **2014**. Getting out of Supply Management. Retrieved June 20, 2015, from http://www.conferenceboard.ca/press/speech_oped/14-03-11/getting_out_of_supply_management.aspx

Tiffin, R., and Balcombe, K. 2011. The determinants of technology adoption by UK farmers using Bayesian model averaging: the cases of organic production and computer usage. *Australian Journal of Agricultural and Resource Economics*, 55(4), 579–598.

Tiffin, R., and Tiffin, A. 2005. The Adoption and use of Computers in Agriculture in England and Wales. *University of Reading*. Retrieved from http://www.personal.rdg.ac.uk/~aas00jrt/wps/comp.pdf on March 20, 2014

Tweeten, L. G. 1992. *Agricultural trade: Principles and policies*. Westview Press Boulder, Colorado.

Valacta Inc. 2012. Valacta Overview. Retrieved January 17, 2015, from http://www.valacta.com/EN/our-company/Pages/default.aspx

VandeHaar, M. J., and St-Pierre, N. 2006. Major advances in nutrition: relevance to the sustainability of the dairy industry. *Journal of Dairy Science*, 89(4), 1280–91.

Verbeek, M. 2004. *A Guide to Modern Econometrics* (2nd ed.). Chichester: John Wiley & Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, England.

Wall, E. H., and McFadden, T. B. 2008. Use it or lose it: enhancing milk production efficiency by frequent milking of dairy cows. *Journal of Animal Science*, 86(13), 27–36.

Warren, M. F. 2002. Adoption of ICT in agricultural management in the United Kingdom: the intra-rural digital divide. *Agricultural Economics*, 48(1), 1–8.

Webb, D. W. 1992. *Artificial insemination in dairy cattle*. University of Florida Cooperative Extension Service, Institute of Food and Agriculture Sciences, EDIS.

Winkelmann, R., and Boes, S. 2006. *Analysis of microdata*. Springer. Retrieved from http://www.urosario.edu.co/Educacion-Continuada/documentos/Contenidos-tematicos/Economia/CT-Analysis-of-Microdata.pdf

Woodburn, M. R., Ortmann, G. F., and Levin, J. B. 1994. Computer use and factors influencing computer adoption among commercial farmers in Natal Province, South Africa. *Computers and Electronics in Agriculture*, 11(2), 183–194.

Yu, X. 2014. Risk Attitudes, Social Interactions and the Adoption of Genotyping in Dairy Production. University of Guelph. Retrieved from https://atrium.lib.uoguelph.ca/xmlui/bitstream/handle/10214/8206/Yu_Xi_201407_Msc.pdf?sequence=1

Zepeda, L. 1990. Adoption of Captial Versus Management Intensive Technologies. *Canadian Journal of Agricultural Economics*, 38(3), 457–469.

Zepeda, L. 1994. Simultaneity of technology adoption and productivity. *Journal of Agricultural and Resource Economics*, 19(1), 46–57.

Zheng, Y. 2013. Adoption of Total Mixed Ration Practice and Profitability: The Case of Ontario Dairy Farms. University of Guelph. Retrieved from https://atrium.lib.uoguelph.ca/xmlui/bitstream/handle/10214/6619/Zheng_Yi_201305_MSc.pdf?sequence=1

APPENDICES

Appendix A: Variance information of imputed variables after imputations

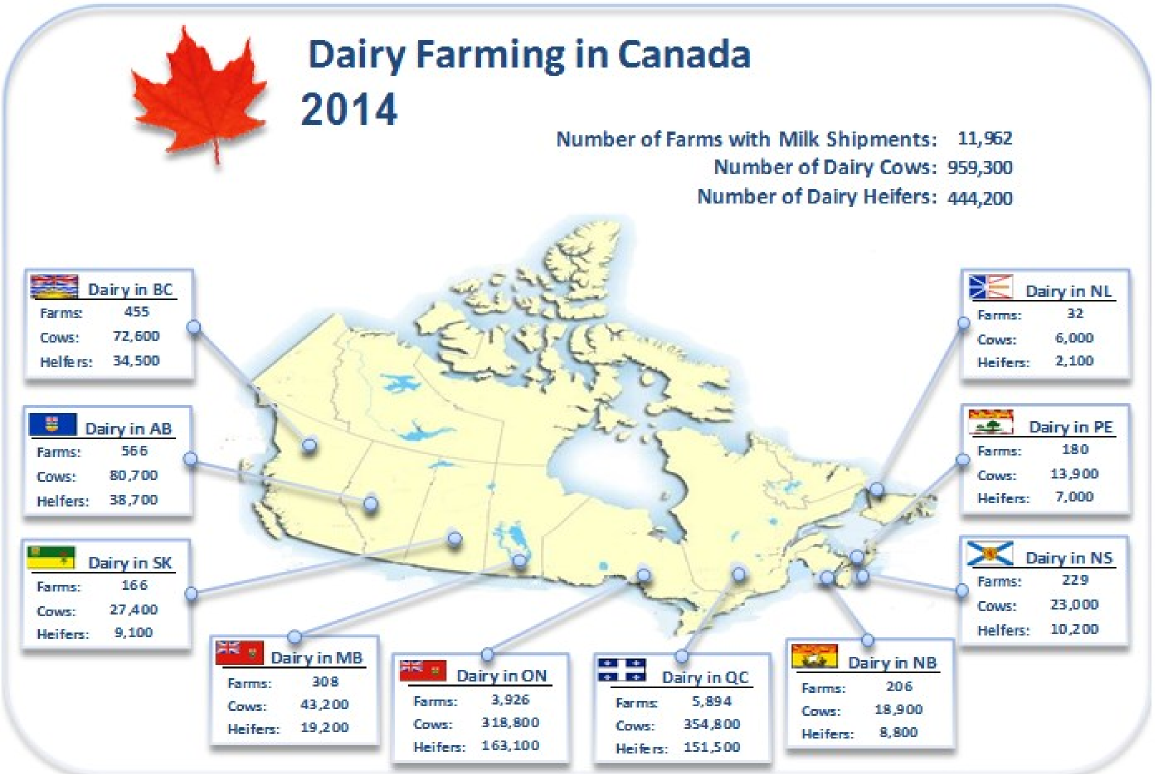
Parameter	Variance			Relative Increase in Variance	Fraction of Missing Information	Relative Efficiency
	Between	Within	Total			
Sex	0.0054	0.5258	0.5314	0.0107	0.0106	99.95%
Succession	0.0875	0.3267	0.4185	0.2811	0.2234	98.90%
Post-secondary Education	0.0065	0.2791	0.2860	0.0244	0.0239	99.88%
Years of experience	0.0000	0.0005	0.0006	0.0786	0.0734	99.63%
Innovativeness	0.0010	0.0701	0.0711	0.0156	0.0154	99.92%
Ownership type	0.0030	0.1097	0.1128	0.0282	0.0275	99.86%
Planning horizon	0.0001	0.0007	0.0008	0.1185	0.1070	99.47%
Off-farm income	0.0000	0.0000	0.0000	0.1357	0.1208	99.40%
Dairy herd size	0.0000	0.0000	0.0000	0.0403	0.0389	99.81%
Percent feed cost	0.0001	0.0002	0.0004	0.5006	0.3413	98.32%
Debt-to-asset ratio	0.0001	0.0002	0.0002	0.4222	0.3033	98.51%
Quota limitation	0.0004	0.0274	0.0278	0.0156	0.0154	99.92%
Cost per hl of milk	0.0001	0.0002	0.0004	0.5462	0.3616	98.22%
Group membership	0.0110	0.2643	0.2758	0.0437	0.0421	99.79%
Future extension plans	0.0154	0.2309	0.2471	0.0702	0.0660	99.67%

Appendix B: Percentage of adopters adopting other technologies

	AIDPB	AIYB	TMR	AISS	GENO	YGBNS	RMS	DHIP	PC
AIDPB		96.57	94.04	97.73	100.00	65.22	85.71	96.67	91.45
AIYB	91.35		89.40	90.91	97.62	69.57	85.71	89.44	85.53
TMR	76.76	77.14		81.82	93.33	78.26	92.86	78.33	76.97
AISS	46.49	45.71	47.68		54.76	43.48	50.00	46.11	44.74
GENO	22.70	23.43	23.18	11.36		26.09	21.43	23.33	21.71
YGBNS	8.11	9.14	11.92	11.36	14.29		7.14	10.00	13.82
RMS	6.49	6.86	8.61	7.95	7.14	4.35		6.67	8.55
DHIP	94.05	92.00	93.38	94.32	100.00	78.26	85.71		89.47
PC	75.14	74.29	77.48	77.27	78.57	91.30	92.86	75.56	

- Figures highlighted in green show technologies where more than 60% of the adopters adopt all the other technologies

Appendix C: Distribution of dairy farms and herds in Canada - 2014



Source: Canadian Dairy Commission:
http://www.dairyinfo.gc.ca/index_e.php?s1=dff-fcil&s2=farm-ferme&s3=nb